DETERMINANTS OF HOW UNDERGRADUATE STUDENTS ATTEND TO AND PERCEIVE FEATURES OF ELECTIVE COURSES

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Mark B. Wolf

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DETERMINANTS OF HOW UNDERGRADUATE STUDENTS ATTEND TO AND PERCEIVE FEATURES OF ELECTIVE COURSES

Approved by:

Dr. Phillip L. Ackerman, Advisor
School of Psychology
Georgia Institute of Technology

Dr. Ruth Kanfer, Advisor
School of Psychology
Georgia Institute of Technology

Dr. Lawrence R. James
School of Psychology
Georgia Institute of Technology

Dr. Richard Catrambone
School of Psychology
Georgia Institute of Technology

Dr. Gary J. Lautenschlager
Department of Psychology
University of Georgia

Date Approved: July 6, 2009

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SUMMARY

Across the lifespan, individuals make repeated course selection decisions. As Ackerman (1996) and others (e.g., Babad, 2001; Kerin, Harvey, & Crandall, 1975) have suggested, students' course selection decisions may importantly affect their academic and career success. Although there has been some research on the situational determinants of course selection decisions, there has been surprisingly little systematic research to date examining the role that individual differences may play in determining how the characteristics of a course (e.g., class size, difficulty) influence individuals' course selection decisions. Two studies (a pilot study and a main study) were conducted to examine the influence of individual differences in reward sensitivity and punishment sensitivity on course selection preferences.

The pilot study was conducted to determine the course features associated with individuals' standings on punishment sensitivity and reward sensitivity. Based on the results of the pilot study, course descriptions were developed for the main study that resemble the layout of websites designed to help students select courses based on comments made by other students. To investigate the hypothesis that individual differences in punishment sensitivity and reward sensitivity influence course selection preferences in the main study, the comments included in the course descriptions were manipulated to describe course features that were either aversive, appetitive, or neutral.

The results of the main study tended to conform to the predictions made in the hypotheses. Consistent with Reward Sensitivity Theory, participants with a higher standing on punishment sensitivity were more likely to rate course descriptions more negatively on a negatively-toned rating scale than participants with a lower standing on

punishment sensitivity and participants with a higher standing on reward sensitivity were more likely to rate course descriptions more positively on a positively-toned rating scale than participants with a lower standing on reward sensitivity. An examination of the predictive efficiency of the interaction between punishment and reward sensitivity supported the presence of interaction effects; however, the nature of the effect was inconsistent across samples and predictor pairs. In addition, although participants rated courses with more aversive features more negatively and courses with more appetitive features more positively, the results from multilevel modeling analyses indicated that punishment sensitivity and reward sensitivity continued to predict course selection preferences in models that also included the emotional-tone (aversive, appetitive, or neutral) of the comments in the course descriptions as variables. Cross-level interactions of punishment and reward sensitivity with the patterns of comment valences did little to improve model fit.

Inherent in the hypotheses of the main study was a boundary condition that punishment sensitivity would only predict ratings when a course description included aversive comments and reward sensitivity would only predict ratings when a course description included appetitive comments. The comment structure of the course descriptions did not appear to moderate the predictive efficiency of punishment sensitivity or reward sensitivity. However, in general, the results did suggest that individuals' standing on punishment sensitivity was associated with viewing courses in terms of negative features and reward sensitivity was associated with viewing courses in terms of positive features. The results support the conclusion that punishment sensitivity is associated with a tendency to perceive courses more negatively in terms of the aversive features of the course and reward sensitivity is associated with a tendency to perceive courses more positively in terms of the appetitive features of the course. To provide a more comprehensive assessment of course selection preferences from respondents with higher standings on punishment sensitivity and reward sensitivity, the results suggest that scales should include items that address both the negative and positive features of courses.

CHAPTER 1

INTRODUCTION

Individuals wishing to further their education often engage in a process of selecting one or more courses. College students typically select courses to fulfill requirements to complete a major, a minor, and core course requirements. In addition, students are also often given the opportunity to select a number of approved elective courses. Beyond college, individuals who wish to gain additional skills and knowledge are usually required to select from a list of courses based upon their career goals, aspirations, or general interests. For example, employees who seek to develop their computer skills often must select from among a wide range of computer skills training courses. Similarly, adults who seek to develop non-work competencies during their leisure time may select from a wide range of courses offered in the local community.

Clearly, individuals' course choices are strongly influenced by course content. A substantial amount of research has been conducted on course selection decisions made based on course content, such as students preferences with respect to taking mathematics or English courses (Marsh & Yeung, 1997; Meece, Wigfield, & Eccles, 1990). However, beyond course content, relatively little is known about how the features of a course influence course selection decisions (Babad, 2001; Babad, Darley, & Kaplowitz, 1999). For example, even within a content area, such as math, specific course features such as class size and instructor teaching style may play a pivotal role in course selection. Similarly, among working adults, course selection may be largely determined by perceptions of how difficult the course will be or how likely the individual is to succeed in the course.

A small, but disparate body of research has been conducted examining feature based course selection (e.g., Babad, 2001; Babad, Darley, & Kaplowitz, 1999; Kerin et al., 1975). In the psychological and management literatures, research on feature based course selection preferences has focused on how ratings and rankings of different course features are broadly related to course preferences among college students and personality characteristics that are associated with a preference for specific course features. In contrast, research in the field of economics has investigated the influence of course features on student selection decisions to address specific enrollment problems. For example, two studies from economics journals sought to address why enrollment in economics courses was declining (Fournier & Sass, 2000; Sabot & Wakeman-Linn, 1991). In these two studies, the researchers investigated the probability that a student would enroll in a class (or sequence of classes) based on the characteristics of the students and specific features of the classes. The failure of these studies to consider course selection from a broader, psychologically-oriented decision-making perspective has made it difficult to integrate the disparate findings on how course features affect course selection.

As Babad and his colleagues (Babad, 2001; Babad et al., 1999) noted, selecting a course necessitates a decision-making process that takes into account one or more alternatives, with each alternative having a different set of expected outcomes. Student decision makers must often make a trade-off for certain expected utilities by selecting one alternative over another in order to reach a choice that is the most satisfying at the time. Complicating matters further, individuals tend to select different courses for different reasons. For example, a student may take one class to fulfill a core requirement and another based on interest or career aspirations.

In addition, students often select more than one course at a time. Undergraduate students typically pick about five classes per semester (Szafran, 2001). Students must take into account the viability of their course selections for forming a workable class schedule, and may need to consider how the courses they select will affect their ability to balance their workload and ensure that they complete their major course requirements in a timely manner. As a result, students often have little time to gather information about the relevant courses and tend to use short-cuts to reduce the amount of time and effort required to make a decision (Babad, 2001). In the quest for making decisions quickly, salient features of a course may overshadow other important aspects of a course, and students may utilize less reliable sources of information that are easily obtained rather than expending more effort to gain additional and more reliable information. Further, since many students remain undecided in terms of their educational goals and career aspirations, they may rely on more general interests and preferences than specific information during the course selection process.

An integrated conceptualization of course selection as a decision-making process requires several considerations (Babad, 2001). First, the characteristics of the decision makers (e.g., personality traits, interests) must be considered. Second, the aspects of the courses (e.g., learning opportunity, workload) and the instructors (e.g., domineering, humorous) must be considered. Third, the type of information (e.g., course reviews, word of mouth) and the source of the information (e.g., friends, academic advisors) should be considered. And fourth, situational characteristics (e.g., time constraints, overall workload) are also important. Rather than attempting to examine all four components, the first two characteristics were examined; namely, person characteristics and course features. In contrast to the type and the source of information, person characteristics and course features can be expected to play a role in course selection decisions across a range of contexts and throughout the adult lifespan.

A second and perhaps more important reason for focusing on person characteristics and course features pertains to the potential relationship between these two factors. Specifically, Reward Sensitivity Theory is used to investigate how individual differences in students' sensitivity to punishment and reward influences the aspects of a course individuals attend to and perceive when examining a prospective course. According to Reward Sensitivity Theory and related research (A. Gomez & Gomez, 2002; R. Gomez, Cooper, McOrmond, & Tatlow, 2004; Rusting, 1998, 1999), individuals are posited to process emotionally-valenced stimuli in a manner that is consistent with relatively-stable tendencies toward sensitivity to punishment and reward. As applied to course selection, the theory suggests that students with higher levels of sensitivity to punishment are more likely to attend to the aversive features of a course (e.g., challenging to get a good grade, intellectually demanding) and to perceive these features as more aversive than students with lower levels of sensitivity to punishment. Similarly, students with a higher sensitivity to reward are more likely to attend to the appetitive features of a course and perceive these features as more rewarding than students who have a lower sensitivity to reward. Reward Sensitivity Theory provides an underlying framework from which to derive specific hypotheses regarding how students will attend to and perceive different aspects of courses.

The remainder of this section is organized into three sections. First, the research literature is reviewed that investigated the role of course content in making course selection decisions. In the next section, research is reviewed that examined the impact of course features on course selection decisions. Finally, theory and research on Reward Sensitivity Theory is introduced and reviewed and evidence is provided that supports the role and influence of individual differences in reward and punishment sensitivity on attending to and perceiving emotionally-valenced information.

Content Determinants of Course Selection Preferences

The bulk of the research examining content influences on course selection focuses on the role of self-concept. Two theoretical perspectives have been proposed. Research by Marsh and Yeung (1997) suggest that individuals prefer courses in which the individual holds a positive self-concept for the course content. In contrast, Eccles and her colleagues (Eccles & Wigfield, 2002; Meece et al., 1990) posited that students prefer courses in which the content is associated with high levels of perceived task value. Although these formulations have been applied to a wider range of outcomes than just course selection (e.g., achievement), they provide insight into the broader issue of course selection decisions. A brief review of each perspective follows below.

Marsh's I/E Model. The lack of a correlation between math and verbal self-concepts, which is inconsistent with the high correlation between math and verbal abilities (approximately $r = .4$; see e.g., Ackerman & Wolman, 2007), led Marsh (1986) to develop the Internal/External Reference (I/E) Model. The I/E model posits that verbal and math self-concepts originate from external and internal comparisons. External comparisons occur when individuals compare their self-perceived math and verbal abilities with their perceptions of others' math and verbal abilities. Internal comparisons occur when, for example, individuals compare their own math ability with their own verbal ability. External comparisons are hypothesized to result in a positive correlation between math and verbal self-concept, whereas internal comparisons are posited to result in a negative correlation. The joint operation of both processes leads to the near zero correlation observed in the literature.

The I/E model predicts a positive effect of math and verbal self-concept on math and verbal achievement, respectively, and a negative effect of math self-concept on verbal achievement and verbal self-concept on math achievement (Marsh, 1986). Marsh (1992) has extended the I/E model to cover additional courses, and more recently, Marsh and Yeung (1997) have further extended the model to describe course selection preferences mainly in terms of predicting a positive relationship between self-concept in a particular subject area and a preference for taking courses in that same subject area (see also Dickhäuser, Reuter, & Hilling, 2005).

Eccles' Expectancy-Value Model. Unlike Marsh's (1986) I/E model, Eccles' Expectancy-Value (EV) model was initially designed to predict academic study choices (Eccles & Wigfield, 2002; Meece et al., 1990). In this model, expectancies and values are assumed to have a direct effect on task performance and task choice. Expectancies are defined as individuals' beliefs about their performance on a task. There are four components of task value. Attainment value is defined as the importance associated with doing well on a task. Intrinsic value is defined as the enjoyment an individual derives from working on a task. Utility value is defined as how much the task fulfills personal goals. And finally, cost consists of the negative aspects of engaging in a task, such as the lost opportunity to engage in completing another task. In general, values tend to predict course choices more effectively than expectancies (Dickhäuser et al., 2005; Eccles & Wigfield, 2002; Feather, 1988; Meece et al., 1990; Nagy, Trautwein, Baumert, Köller, & Garrett, 2006).

Both the I/E and EV models rely on a similar set of results for support. Several studies have supported the validity of self-concept in specific school subjects (e.g., mathematics ability perceptions) for predicting students' desire to enroll, intentions of enrolling, and actual enrollment in classes in the same subject areas (Dickhäuser et al., 2005; Feather, 1988; Marsh & Yeung, 1997; Meece et al., 1990; Nagy et al., 2006). For example, Dickhäuser et al. (2005) found that students' self-concept in biology was correlated with a desire to enroll in a biology class the next term (r = .36), and students' self-concept in chemistry was correlated with a desire to enroll in a chemistry class the next term (r = .35). Similarly, Nagy et al. (2006) found that students' self-concept in biology predicted enrollment in an advanced biology course (r = .24) and students' self-concept in math predicted enrollment in an advanced math course (r = .65).

The findings in this stream of research highlight the importance of self-concept as a critical link in the relationship between course content and course selection preferences. Although the I/E and EV models provide different explanations for the basis of self-concept, the empirical findings show that an individual's self-concept with respect to the course content is a potent predictor of course selection preference. What remains unclear, however, is whether and how course features influence course selection. Research on this issue is discussed next.

Feature Determinants of Course Selection Preferences

Research on course selection decisions made based on the features of a course overlaps with the research on the content of a course, as course relevance is a common attribute of a course that is examined. However, students are often asked to provide a more general rating of the relevance of the course with respect to their interests or major or a characteristic of a course in general, and not to rate courses in different subjects. Research on course features focuses on the characteristics of the instructor (e.g., humorous) and characteristics of the class experience (e.g., strict attendance policy, heavy reading load). At times it is difficult to separate features of a course and the characteristics of an instructor as the instructor tends to determine course features as well. However, some features of a course may be beyond the control of the instructor (e.g., class size). In contrast to research examining how students select a course based on the content of a course, a systematic inquiry into how students select a course based on the features of a course has not yet developed. As a result, the research reviewed below is not well integrated. The studies come from a variety of disciplines including psychology, management, and economics. Each discipline has adopted a different approach with a different set of data analytic methods. Studies conducted in the psychological and management literatures typically ask students to provide ratings and rankings of courses and course features, resulting in summary scores in the form of averages. Several psychological studies have examined the influence of personality and learning styles on preferences for different assessment methods, teaching methods, and instructor characteristics. Some research in the management domain has used conjoint analysis to examine the configuration of course features that students tend to prefer. In contrast, studies in the economics research literature typically estimated the probability that a student would enroll in a class or a sequence of classes based on student characteristics, class characteristics, and characteristics of classes already taken by the student. A sample of studies illustrating each of these approaches and their findings is described briefly below.

In an attempt to better predict why students select specific courses, Kerin and his colleagues (1975) asked one-hundred general business undergraduates to rate twelve pre-selected business electives on difficulty, relevancy to area of study, and their intentions to enroll in the courses. The researchers found that perceived course difficulty did not distinguish between those who intended to enroll from those who did not, except for one class in which most of those who planned to enroll in the course rated it as more difficult. In contrast, however, for the majority of the courses, students who rated the course as more relevant were more likely to express intentions of enrolling in the course. Descriptive findings based on an analysis of student rankings for eight course characteristics in terms of the importance of the characteristic for making a course selection decision showed that personal interest (38%), course content (26%), and comparability with major field (22%) were considered the most important course features. In contrast, instructor (7%), time the course was offered (4%), workload (1%), course availability (1%), and balancing workload (1%) were considered substantially less important. These results suggest that the content of a course is more important than the features of a course.

In a similar study, Roberts (1981) investigated the features that contribute to a successful course. The final list of twenty-five teaching dimensions were based on 19 teaching exemplars, which had been taken from a broad sample of student course evaluations that were classified as contributing to overall teaching success. Ninety-nine students were asked to rank the importance of each dimension and to rank order the 10 most important dimensions. Roberts found that the most important features of instruction included a good command of the subject, an interesting presentation, a reasonable workload, and fair and impartial grading. The lowest-rated dimensions included the instructor is uninformed in other disciplines, the instructor presents material not included in the text, and the overall intellectual atmosphere. Consistent with these findings, student interviews conducted after the questionnaire indicated that many students focused on course features that would lead to a higher grade as opposed to a focus on the overall intellectual value of the course. That is, Roberts found that higher intellectual quality was only tolerated if it did not interfere with obtaining a higher final grade.

In another study on course selection preferences, Babad and Tayeb (2003) asked 1,007 students to select five courses they would like to take from a list of 12 courses. Each course was described in three sentences varying in learning value (high or low), lecture quality (high or low), and level of difficulty (high, moderate, or low). Students were instructed to assume that all of the courses were the same in all other respects. Analysis of the five courses selected by most of the students showed a preference for courses that had a high learning value (72%), high lecture quality (67%), and low difficulty (55%). Similarly, students avoided courses with high difficulty and low learning value. In contrast to the study by Roberts (1981), Babad & Tayeb (2003) found that grading leniency was less important to students than learning value. Babad & Tayeb (2003) also found that students' age and GPA were significantly related to a preference for higher leaning value ($r_{\text{age}} = .09$, $r_{\text{grades}} = .07$) and greater difficulty ($r_{\text{age}} = .16$,

$r_{\text{grades}} = .11$), but that only age was related to a preference for high quality lectures ($r_{\text{age}} = .10$, $r_{\text{grades}} = .04$).

Babad (2001) also examined the determinants of elective course selection using a retrospective procedure in which 650 upper-class undergraduates were asked to recall elective courses they had selected the previous semester. Students were then asked to concentrate on the first and last courses they choose, to answer questions related to those course selection decisions, and to rate the importance of 22 factors in making their decisions on whether or not to take those first and last courses. Babad (2001) found that the most important factors in course selection for the first courses selected were topic interest, course contribution to personal development, clear and understandable lectures, comfortable day and hour, exciting lectures, number of credits fit need, professor is an expert, highly intellectual, interesting assignments, and contribution to work aspirations. The most important considerations for the last course included comfortable day and hour, number of credits fit need, easy to get high grades, easy assignments, has preferred exam format, and optional attendance. Other than preferences for a comfortable day and hour and the number of credits fit need appearing on the list for the first and last courses, Babad found that the lists of most important preferences for first and last course selections were different. In particular, factors rated as most important in first course preferences tended to focus on the intellectual value of the course. In contrast, factors rated as most important in last course preferences were more directed toward a grades focus and avoiding work. These results support the notion that students adopt different decision criteria for course selection when constructing a course schedule for a semester.

Wilhelm (2004) implemented a choice-based conjoint analysis to examine the influence of four course features on students' course preferences. Students were asked to select from among two courses that varied in level of grading leniency, course usefulness, workload, and teacher ratings. The results obtained showed that although evaluations (24%, χ = 39.3, $p < .01$) and course workload (7%, χ = 20.2, $p < .01$) significantly influenced students' course decisions, the relative importance[1] of course usefulness (38%, χ = 109.3, $p < .01$) and grading leniency (31%, χ = 108.7, $p < .01$) had a more pronounced effect. Students were willing to select a course with poor course evaluations or a heavy workload if the course offered the opportunity to acquire a large amount of useful knowledge. The most highly preferred configuration of attributes denoted a class that was highly useful with lenient grading standards, an instructor that received excellent evaluations, and a moderate workload. Although the importance of grading leniency was rated highly by students, the usefulness or worth of the course was more important, further suggesting that students had a slightly higher learning value focus than grade focus.

Using a similar research design, Taylor, Humphreys, Singley, and Hunter (2004) employed conjoint analysis to investigate the importance of a web course management system and four other course features. The importance of the course features differed by student class. Lower-level students preferred fewer in-class writing assignments (28.6%), followed by more tests (26.5%), no group projects (25.9%), the use of a web course management system (18.8%), and many guest speakers (0.2%). This configuration of results suggests that more junior students expect and prefer the use of tests as the primary grading mechanism, at least compared to the other course features

[1] "The relative importance of each attribute was calculated by computing the difference between the largest and smallest part-worth for each attribute, summing the differences and normalizing to 100" (Wilhelm, 2004, p. 23).

included in the study. In contrast, upper level students preferred the use of a web course management system (34.1%), followed by fewer in-class writing assignments (31.5%), the absence of group projects (26.4%), more tests (5.1%), and many guest speakers (2.9%). The importance of tests dropped dramatically for the senior level students in favor of the use of a web course management system. These findings may be interpreted to suggest that upper level students prefer other grading mechanisms than tests and more sophisticated course management practices.

Three studies with samples from several countries (Australia, Britain, and the United States) have examined the influence of personality and learning style, among other variables, on assessment preferences (Chamorro-Premuzic, Furnham, Dissou, & Heaven, 2005; Furnham & Chamorro-Premuzic, 2005a; Furnham, Christopher, Garwood, & Martin, 2008). The cumulative findings of the studies support the influence of personality characteristics on preferences for different assessment methods. Extraversion was associated with a preference for oral examination and group work. In contrast to the other personality characteristics, Neuroticism was the only personality characteristic that was negatively associated with assessment preferences including a desire for avoiding classes that use essay exams, oral exams, and coursework administered throughout the semester. Conscientiousness was associated with a preference for coursework and final projects. The results for Agreeableness and Openness were inconsistent and require further research.

One of the studies examined the association between learning styles and assessment preference using Biggs' (1987) Study Process Questionnaire, which includes three dimensions (Furnham et al., 2008). A surface learning style is associated with goal oriented approaches as opposed to satisfying intrinsic interests and is associated with superficial learning strategies (e.g., rote memory). A deep learning style is associated with an attempt to meaningfully understand course content to satisfy intrinsic interests. An achieving learning style is associated with taking a systematic approach to achieving high grades. A series of stepwise regressions indicated that learning styles were more important determinants of assessment preference than personality characteristics. A surface learning style was related with a preference for multiple choice exams and group work and a preference for not having essay exams or final projects. Somewhat conversely, a deep learning style was related with a preference for essay exams, final projects, and oral exams and a preference for not having multiple choice exams. Similarly, an achieving learning style was related to a preference for final projects, oral exams, and coursework and a preference for not having multiple choice exams.

A similar study (Chamorro-Premuzic, Furnham, & Lewis, 2007) examined the association of personality characteristics and learning styles with different teaching methods using a sample of 221 British medical students (see also Zhang, 2004, 2007). Agreeableness, Openness, and a deep learning style were associated with a preference for lab work, small class sizes, a clinical teaching approach, and the use of discussion groups; conversely, Neuroticism and a surface learning style were associated with a preference for a class without those teaching methods. Conscientiousness was related a preference for a clinical teaching approach and Extraversion was associated with a preference for not having independent study.

Taken together, the research on assessment methods and teaching methods converge upon some general themes related to personality and learning style. As would be expected, Extraversion was related to a preference for face-to-face interactions with instructors and students. Neuroticism was associated with a preference to avoid anxiety provoking situations. Conscientiousness and an achieving learning style were associated with a preference for consistent and routine assessment and teaching practices. A surface learning style was associated with a preference for putting forth as little effort as possible to obtain a final grade. On the other hand, a deep learning style was associated with a preference to demonstrate oneself and an intrinsic interest to engage in learning. Although inconsistent, Agreeableness and Openness were associated with a general preference for a variety of assessment and teaching methods.

Several studies examined students' preferences for an instructor based on instructors' personalities as well as the relationship between students' personality and the preference for their instructors' personality (Chamorro-Premuzic, Furnham, Christopher, Garwood, & Martin, 2008; Furnham & Chamorro-Premuzic, 2005b; Swami et al., 2007). Across these studies, students tended to prefer instructors who are highly Conscientious, Extraverted, and Agreeable but not Neurotic. Two trends were evident across the studies (Chamorro-Premuzic et al., 2008; Furnham & Chamorro-Premuzic, 2005b). Other than Neuroticism, there did seem to be a relationship between a students' personality and a preference for an instructor with the same personality characteristic. Those higher on Extraversion, Openness, and Agreeableness preferred an instructor who was not high on Neuroticism. Consistent with the general theme discussed above for the research examining assessment and teaching methods, a surface learning style was related to a preference for an agreeable and conscientious instructor and a deep learning style was associated with a preference for an instructor who was high on Openness. The convergent relations for an achieving learning style were inconsistent.

Exploring the decline of enrollment in economics classes, two papers from the field of economics explored the probability that a student would enroll in a course given aspects of the student, aspects of the course, and aspects of courses previously taken by the student in the same department. The first study examined the probability that a student would take a second course in the same department based on the grade the student received in the first course (Sabot & Wakeman-Linn, 1991). The statistical model also included the department of the students' intended major, the students' gender, and the students' level of need for achievement as control variables. The higher the grade received in the first course taken in a department, the more likely the student was to enroll in another class in the same department. As a result, departments with more lenient grading standards had a greater likelihood that students would take a second class in their departments. The second study examined the probability that students would complete two economics courses (microeconomics and macroeconomics; Fournier & Sass, 2000). Students were more likely to complete both courses if they scored higher on a standardized mathematics exam (probit estimate for those not required to take both classes = .0015, $p \leq .05$) and if they completed the first course earlier in their college careers (credits earned prior to both classes probit estimate for those not required to take both classes = -.0015, $p \leq .05$).

In summary, although the breadth of the studies relevant to this area of research limits the conclusions that may be drawn, a number of general themes are evident. Consistent with the research examining course preference based on the subject matter of a course (e.g., Nagy et al., 2006), some of the research discussed above also found that the relevance of the course to college or career goals directed students to prefer courses covering particular subject areas. In addition, for many of the studies discussed above, the pattern of course selection preferences could be summarized in terms of either a grade focus or a focus on learning value. Several studies operationalized and examined the predictive validity of a grade focus as a preference for using a surface learning style and a learning value focus as a preference for using a deep learning style (Chamorro-Premuzic et al., 2007; Furnham et al., 2008).

Although the factors that determine a grade focus or learning value focus are not well delineated, this body of research does reveal a number of predictors. The consistent findings across a pair of studies conducted by Chamorro-Premuzic et al. (2007) and Furnham et al. (2008) suggest that a preference for a surface learning style was correlated positively with Neuroticism and negatively with Openness, and a preference for a deep learning style was correlated with Openness, Conscientiousness, and Agreeableness. In addition, older and more senior students tended to adopt a learning value focus. And classes selected first in a students' schedule appear to be selected based on a learning value focus as opposed to the last course, which tended to elicit a grade focus. The difference between a learning value focus versus a grade focus appears to be an important theme across studies examining course selection preferences.

Reward Sensitivity Theory

Trait congruency hypothesis. A common approach used by researchers to find consistencies in the way that people process emotional stimuli has been to examine trait congruent processing (Rusting, 1998). The trait congruency hypothesis holds that individuals process information in a manner that is consistent with their standing on personality traits. Researchers have compared individuals' standing on personality traits to how they perceive, attend to, interpret, judge, recognize, and recall emotionally-valenced stimuli. The Reward Sensitivity Theory provides a rationale for the trait congruency hypothesis (Rusting, 1999).

Based on animal learning research and anti-anxiety drug manipulations, Gray and his colleagues developed what has become known as the Reward Sensitivity Theory to describe the function of neuropsychological systems that affect emotion, motivation, and learning (Corr, Pickering, & Gray, 1997; Gray, 1978, 1987; Gray & McNaughton, 1996; Gray, Owen, Davis, & Tsaltas, 1983; Pickering, Dfaz, & Gray, 1995; Pickering & Gray, 1999; Wilson, Barrett, & Gray, 1989). Although Gray's initial work was not concerned with personality, the development of the theory over time has provided descriptions of systems underlying the expression of Anxiety and Impulsivity, which have proven useful to personality researchers (Smillie, Pickering, & Jackson, 2006). In fact, several self-report measures have been derived from the Reward Sensitivity Theory (e.g., Ball & Zuckerman, 1990; Carver & White, 1994; Torrubia, Ávila, Moltó, & Caseras, 2001).

The use of Gray's theory as a basis for assessing aspects of personality has diverged from research examining the function of neuropsychological structures and related behaviors, and the research from these two areas has become increasingly difficult to reconcile (Smillie, Pickering et al., 2006). As the study proposed in this paper involves the examination of the personality domain, the literature review will focus on the Reward Sensitivity Theory as it relates to the expression of Anxiety and Impulsivity. The trait congruency hypothesis will be examined using the personality system derived from the Reward Sensitivity Theory. The Reward Sensitivity Theory proposes the existence of two systems: the Behavioral Inhibition System (BIS), which is related to the expression of Anxiety, and the Behavioral Activation System (BAS), which is related to the expression of Impulsivity.

BIS and BAS. Gray and his colleagues have hypothesized the existence of two systems in the brain (Corr et al., 1997; Fowles, 1980; Gray, 1978, 1987, 1994, 1999; Gray & McNaughton, 1996; Gray et al., 1983; Pickering et al., 1995; Pickering & Gray, 1999; Wilson et al., 1989). The BIS was the first of the two systems hypothesized, and is much more extensively delineated. The BIS mediates responses to stimuli that signal punishment, stimuli that signal frustrative nonreward, and extremely novel stimuli. The primary outputs of the system are behavioral inhibition, increased arousal, and increased attention. The theory suggests that individual differences in BIS sensitivity give rise to trait anxiety. Individuals with a greater BIS sensitivity are more susceptible to aversive and frustrative stimuli. Furthermore, Gray and his colleagues have situated Anxiety within the personality space of Extraversion and Neuroticism as defined by Eysenck (1967), and indicated that Anxiety is highly related to Neuroticism and, to a lesser extent, negatively related to Extraversion (Gray, 1994; Pickering, Corr, & Gray, 1999).

A corresponding second system, the BAS, was hypothesized to reflect a sensitivity to reward and nonpunishment (Fowles, 1980; Gray, 1987, 1994; Gray et al., 1983; Pickering et al., 1995; Pickering & Gray, 1999; Wilson et al., 1989). BAS is situated orthogonally to BIS in the Extraversion/Neuroticism personality space, such that higher levels of BAS correspond to higher levels of Extraversion and, to a lesser extent, higher levels of Neuroticism. Activation of the BAS is characterized by approach behaviors or active avoidance. This system is hypothesized to underlie the trait of

Impulsivity in much the same way as the BIS underlies Anxiety. Although Impulsivity may be narrowly defined as acting quickly without deliberation, BAS functioning is associated with the Venturesomeness and Sensation Seeking aspects of Impulsivity in a broader conceptualization of the trait (Pickering & Gray, 1999). However, more recent research (Russo, Leone, Lauriola, & Lucidi, 2008) suggests that BAS functioning may be more aligned with Extraversion than Impulsivity (see also Smillie, 2008).

Larsen and Ketelaar (1989, 1991) provided general support for the Reward Sensitivity Theory in two mood induction studies. In the first dairy study, 67 undergraduates completed the Eysenck Personality Inventory. A false feedback mood induction technique was used. After completing an ability test that was described as assessing a fictitious skill, students were randomly given either positive feedback or negative feedback. The dependent measure consisted of a bipolar mood assessment (e.g., Happy-Sad, Comfortable-Relaxed). High scores on the mood assessment were interpreted as Positive Affect. Neuroticism was highly, negatively related to Positive Affect (r = -.30) after the negative mood induction, but not after the positive mood induction (r = -.03), and Extraversion was highly related to Positive Affect (r = .25) after the positive mood induction, but not after the negative mood induction (r = .01).

In the second study, 359 students completed the Eysenck Personality Questionnaire and mood was manipulated using written scenarios. Students were asked to imagine themselves in the scenarios as they read them. Next, students rated themselves on adjectives taken from the Positive and Negative Affect Schedule (PANAS). Similar to the first study, Neuroticism was most highly correlated with Negative Affect (NA) under the negative mood induction (r = .34) and Extraversion was most highly correlated to Positive Affect (PA) under the positive mood induction (r = .32). Both studies demonstrated that those with higher scores on Neuroticism are more susceptible to experiencing NA and those with higher scores on Extraversion are more susceptible to experiencing PA after a congruent mood induction.

Gable, Reis, and Elliot (2000) provided further support using an assessment designed to assess BIS and BAS sensitivity in a pair of dairy studies. Their results support the general association of BIS and BAS sensitivity with a higher susceptibility to experiencing greater NA and PA, respectively. In the first study, 86 undergraduates were administered the BIS/BAS Scales at the beginning of the study and daily mood (the PANAS) and event questionnaires everyday for 14 days. The event questions asked students to report the frequency with which 17 positive events and 19 negative events occurred and to rate the importance of each event. Higher levels of BIS sensitivity were related to higher daily levels of NA and to rating negative events as more important. In addition, those high on BIS sensitivity also reported higher levels of NA on days with a greater frequency of negative events. BIS sensitivity was also negatively correlated with daily PA and BAS sensitivity was positively correlated with PA. BAS sensitivity did not predict importance ratings of positive events as hypothesized by the authors. Computer-generated date-time stamps recorded after the completion of each daily questionnaire indicated a substantial lack of compliance with study protocol.

Another diary study was conducted in an attempt to bolster compliance and to verify the results from the first study (Gable et al., 2000). In the second dairy study, 155 students completed the same measures as the first study over 14 days. Compliance with study protocol was high for the second diary study, and the results generally replicated the findings from the first study. As before, individuals higher on BIS sensitivity experienced greater levels of daily NA and reported greater NA on days that they also reported a greater frequency of negative events. BAS sensitivity predicted average daily PA, and in contrast to the previous study, BAS sensitivity also predicted both the frequency of and importance associate with positive events.

Although the BIS and the BAS are hypothesized to give rise to Anxiety and Impulsivity, respectively, and the terms are often used interchangeably, it is important to distinguish between the two systems and the two traits. Fowles (1987) suggested that an individual's vulnerability or susceptibility to experiencing an emotion is very different from the frequency with which an individual experiences an emotion as assessed by common personality instruments such as the NEO questionnaires or the PANAS (see also Zelenski & Larsen, 1999). For example, an individual who has a high BIS sensitivity and low BAS sensitivity is prone to experiencing episodes of anxiety and may seek to avoid anxiety-provoking situations and thereby experience less anxiety. However, susceptibility to experiencing an emotion and the frequency with which an individual experiences that emotion appear to be highly correlated (Zelenski & Larsen, 1999). On the other hand, past research indicates BAS functioning and trait impulsivity are mediated by different cognitive mechanisms and should not be considered interchangeable concepts (Leone, 2009; Smillie, Jackson, & Dalgleish, 2006).

Several studies have supported the validity of the predictions of the Reward Sensitivity Theory in terms of how characteristics of an individual influence or bias their processing of emotionally-valenced stimuli. Although a vulnerability to an emotion and the frequency with which an individual may experience that same emotion are hard to separate, their separation is an important conceptual distinction in the definition of BIS and BAS functioning. Further theoretical development and research have begun to consider the potential interaction of BIS and BAS functioning.

The separable subsystems hypothesis versus the joint subsystems hypothesis. To address past conflicting research results and the complexities of human behavior, Corr (2001) introduced an approach to considering the interaction between the BIS and the BAS (see also Pickering et al., 1997). Previously, Reward Sensitivity Theory indicated that approach-avoidance conflicts were resolved by an individual's dominant system (Pickering and Gray, 1999). Typically studies compared individuals' level of BIS (or Anxiety) with sensitivities to punishment and individuals' level of BAS (or Impulsivity) with sensitivities to reward without considering an interaction. In general, when examining BIS effects the BAS was ignored, and when examining BAS effects the BIS was ignored. Corr (2001) referred to this approach as the separable subsystems hypothesis, and suggested that the joint subsystems hypothesis may more effectively account for certain study effects.

The separable subsystems hypothesis is most tenable with simple reward conditions that do not mix signals of reward and punishment, studies that do not shift rapidly back and forth through reward and punishment conditions, studies without strong appetitive or aversive stimuli, and studies with individuals who have high levels of either BIS sensitivity or BAS sensitivity (Corr, 2001, 2002). Under more complex reward conditions that mix reward and punishment, the BIS and BAS most likely exert an interdependent effect as suggested by the joint subsystems hypothesis. Under the joint subsystems hypothesis, the BIS and the BAS may influence behavior resulting from stimuli that signal either reward or punishment. In general, high levels of one system are posited to exert an inhibitory effect on the other system.

Corr (2002) first tested the joint subsystems hypothesis in a pair of studies. In the first study, the startle reflex of 70 college students was measured in response to an acoustic startle probe presented while participants viewed pleasant, unpleasant, and neutrally-valenced slides. In support of the joint subsystem hypothesis, participants scoring high on Anxiety showed a greater startle reflex while viewing the neutral and unpleasant slides unless they were also high on Impulsivity. The results failed to support the expected relation between Impulsivity and startle reflex while viewing the pleasant slides. However, the acoustic startle reflex paradigm is most likely somewhat biased against appetitive responses as the startle probe is inherently aversive.

The second study used a rapid visual information processing task, in which participants indicated when a string of numbers appearing on a computer screen were all even or odd (Corr, 2002). Participants were either given a caffeine pill or a placebo and either given feedback or given feedback and lost money for incorrect answers. Although the results ran counter to predictions, the joint subsystems hypothesis provided a better interpretation of results than the separable subsystem hypothesis. Those high on Impulsivity and low on Anxiety had the most false alarms. In general, both experiments were consistent with a joint subsystems approach and failed to support the predictions of the separable subsystems hypothesis.

Two recent studies have provided additional support for the joint subsystems hypothesis (e.g., Jackson & Francis, 2004; Kambouropoulos & Staiger, 2004). In a study on religiosity, for example, at a distal level Impulsivity independently predicted rewarding attitudes toward religion and Anxiety independently predicted anxious attitudes toward religion (Jackson & Francis, 2004). At a proximal level, rewarding attitudes toward religion predicted a composite of amount of prayer, church attendance, and ratings of church importance, and anxious attitudes toward religion had both a direct effect on the composite outcome and was mediated by rewarding attitudes toward religion supporting a proximal, joint effect.

In the second study, college students completed the Sensitivity to Punishment and Sensitivity to Reward Questionnaire, the Card Arranging Reward Responsivity Objective Task (CARROT), and a computerized and slightly modified version of the Q-TASK (Kambouropoulos & Staiger, 2004). The CARROT provides an assessment of behavioral responses to reward. The speed with which participants sort cards is compared between a baseline condition and after being offered a small financial incentive. Q-TASK was designed as an index of behavioral inhibition induced by punishment. Participants are asked to respond as quickly as possible to a string of letters except if the letter Q is present. Participants receive five points for a correct response and loose ten points if responding when the letter Q is present. In a second phase, strings of letters and numbers are presented, and participants' are asked to respond as quickly as possible except when a number is present. Inhibition is assessed in the second phase by comparing participants' reaction time in Q absent trails versus Q present trails when only letters were present. Sensitivity to Reward predicted CARROT performance and Sensitivity to Punishment predicted inhibition on Q-TASK. In support of the joint subsystems hypothesis, although not in the direction predicted, those higher on both Sensitivity to Reward and Sensitivity to Punishment experienced more inhibition than those low on both sensitivities. A similar pattern of results was evident for CARROT, but not significant. Although the interdependent nature of BIS and BAS appears to be not well understood, research evidence supports the need to look for interaction effects as suggested by the joint subsystems hypothesis.

In addition, results from earlier studies that were originally interpreted as inconsistent with Reward Sensitivity Theory, may now conform to predictions made under Corr's (2001) joint subsystems hypothesis. For example, Zinbarg and Revelle (1989) conducted four experiments using a go—no-go discrimination learning task. Participants were presented with one or two capital letters and were either rewarded for responding to a cued response, punished for not responding to a cued response, rewarded for withholding a response from a non-cue trail, or punished for responding to a non-cue trail. Under Reward Sensitivity Theory, Impulsivity was hypothesized to predict learning when a reward was possible, and Anxiety was hypothesized to predict learning when punishment was possible. However, the most robust finding across the experiments was a cue type by Impulsivity by Anxiety interaction. Similar to the previous two studies discussed above, the direction of the effect in the three-way interaction did not always conform to Reward Sensitivity Theory predictions. Zinbarg and Revelle (1989) hypothesized that the discrepancy in the direction of the effect may have occurred because the cue type varied within experiments and learning a cue type in one block of trails may have transferred to later blocks of trails.

Historically, the Reward Sensitivity Theory was examined only in terms of the separable subsystems hypothesis. Ignoring the potential interactive effect of BIS and BAS sensitivity may lead researchers to miss important findings in their results.

Although the interactive effects of BIS and BAS sensitivity are not well understood in terms of predictions made based on the joint subsystems hypothesis, it is important to examine whether an interaction effect qualifies the individual influence of the BIS and BAS effects. In addition, further examination of the joint subsystems hypothesis may lead to a better understanding of the interactive influence of BIS and BAS functioning in terms of how individuals process emotionally-valenced stimuli.

Processing emotional stimuli. Many studies have supported a relationship between trait anxiety and a bias toward processing threatening or aversive stimuli. For example, individuals with higher levels of Anxiety generated a greater number of threat related words than neutral words and a smaller number of positive words than neutral words from homophones (e.g., die/dye, won/one) presented over a tape player (Byrne & Eysenck, 1993; Dalgleish, 1994; Mathews, Richards, & Eysenck, 1989), imposed threatening meanings on ambiguously worded sentences (M. W. Eysenck & Mogg, 1991; MacLeod & Cohen, 1993), estimated viewing greater frequencies of threatening words (Kverno, 2000), attended to the location where a threatening word appeared longer (MacLeod, Mathews, & Tata, 1986), selectively recalled more threatening words than positive or neutral words (Mathews, Mogg, May, & Eysenck, 1989), classified emotionally ambiguous facial expression as expressing fear (Richards et al., 2002), detected angry faces faster than neutral faces (Byrne & Eysenck, 1995), selectively recalled more negative information and less positive information about themselves (Breck & Smith, 1983; O'Banion & Arkowitz, 1977), and selectively recalled more unhappy than happy personal memories (Mayo, 1989). Only two of these studies also examined a positively-toned emotional trait. Byrne and Eysenck (1993) found that

Extraversion was not significantly correlated with generating a greater number of positively-valenced words than neutrally-valenced words from homophones presented over a tape player, and Mayo (1989) found that Extraversion was positively correlated with recalling more happy personal memories. In an earlier study by Mayo (1983), he also found that Extraversion was positively correlated with retrieving pleasant and happy personal memories. Although a few studies have reported nonsignificant results (e.g., Okun, Stock, Snead, & Wierimaa, 1987), there appears to be ample support for trait congruent processing, especially for negatively-toned traits predicting negatively-valenced processing. For a more comprehensive review of this area of research see Eysenck (1997), MacLeod (1999), Mogg and Bradley (1999), and Rusting (1998).

Moreover, researchers have demonstrated that, although participants tend to show a bias in processing negatively-valenced stimuli in general, individuals with a higher standing on negatively-toned traits tend to show a more pronounced effect when processing negatively-valenced stimuli in particular. For example, in a study with 159 college students, participants were placed into two groups based on a median split using scores from the State-Trait Anxiety Inventory (trait only). The results indicated that although participants estimated seeing a greater number of threatening words than neutral words, the effect was more prominent for the high anxious group (Kverno, 2000). On the recognition task, both groups made more false alarms for the threat words than the neutral words; however, the high anxious group made even more false alarms than the low anxious group. In the recall task, both groups recalled a greater number of threatening words and the interaction effect by group was not significant.

Another study recruited 25 participants using an extreme groups design from scores on the trait scale of the State-Trait Anxiety Inventory to examine the detection of faces with different emotional expressions (Byrne & Eysenck, 1995). Together, the participants detected happy faces in neutral crowds faster than angry faces in neutral crowds, and the high anxiety group detected the angry faces more quickly than the low anxiety group. The participants were also able to detect happy faces in neutral crowds faster than happy faces in angry crowds, and the high anxiety group was significantly slower when the crowd consisted of angry faces than the low anxiety group. And finally, in general, the participants detected happy faces in angry crowds and angry faces in happy crowds at about the same rate. However, the high anxiety group located the angry face in the happy crowd faster than the happy face in the angry crowd, whereas the low anxiety group performed similarly in both conditions.

In a third study, 72 students were recruited from the University of Waterloo (UW) in Waterloo, Ontario and 71 students were recruited from the University of Toronto (UT) in Toronto, Ontario (Quilty, Oakman, & Farvolden, 2007). Participants were presented with pictures from the University of Waterloo and pictures from other Ontario universities (Guelph University and the University of Toronto Scarborough Campus) to examine the connection between familiarity and BIS/BAS functioning. On average, the ratings for the UW participants were higher than the ratings from the UT participants, and the UW pictures were rated more highly by UW participants than the pictures from the other Ontario universities. Furthermore, UW participants who had higher scores on both the BIS scale from the BIS/BAS Scales and Sensitivity to Punishment from the Sensitivity to Punishment and Sensitivity to Reward Questionnaire had an even greater preference for the UW pictures than lower scorers. In general, these three studies demonstrated, although the valence of stimuli may affect participant's behavior, that a more pronounced effect is associated with negatively-toned traits including both anxiety and BIS sensitivity. As stated above, less focus has been placed on examining positively-toned traits. Of the three studies, only Quilty et al. (2007) examined the effect of positively-toned traits, but did not find any significant results.

Rusting (1999) has extended this general area of research in a more systematic manner by examining both states and traits, including both positively- and negatively-toned traits, and using multiple tasks with the same sample (see also Rusting & Larsen, 1998). Rusting (1999) conducted a pair of studies examining trait and mood congruent processing. In the first study, undergraduate students completed mood and trait versions of the PANAS, the Eysenck Personality Questionnaire, and three emotional processing tasks. In the first task, students were played 16 homophones over a tape player and asked to spell the words. Eight of the homophones had either a positive or neutral meaning (e.g., rose/rows) and the other eight had either a negative or neutral meaning (e.g., bored/board). Students were asked to write a story based on emotionally ambiguous sentences (e.g., "John is resting his head on his hands.") in the second task. Story content was rated for emotional valence. In the third task, students were asked to rate the pleasantness of 36 words as either positive, neutral, or negative. Immediately after completing the ratings, participants were asked to recall as many of the words as possible in three minutes. Extraversion, Positive Affect, and Positive Mood were significantly positively related to writing positive meanings in the homophone task, writing positively-toned story content, and recalling positively-valenced words, and

Neuroticism and Negative Affect were positively and significantly related with the negatively-toned outcomes.

To examine the interaction between the traits and mood states, a series of hierarchical regressions were run with a trait and the corresponding emotionally valenced mood state entered simultaneously in the first step and their interaction term entered in the second step (e.g., Step 1 enter Extraversion and Positive Mood, Step 2 enter Extraversion × Positive Mood). In all but one model the personality trait was a significant predictor and the mood state was not in the first step, and in the second step, the interaction term was never significant. The results provide general support for trait congruent processing under the separable subsystems hypothesis, and not for a mood congruent effect.

A second study was conducted with 83 undergraduates using a similar design except that a mood induction was implemented (Rusting, 1999). The participants were asked to read and imagine themselves experiencing a series of positive or negative events unfolding in a series of short vignettes. To extend the duration of the mood induction, pleasant or unpleasant music corresponding to the initial mood induction was played throughout the study in the background. The pattern of correlations between the traits, moods, and task outcomes was similar to the first study. However, there were two main differences in the results for the hierarchical regressions. First, mood tended to be a significant predictor in contrast to the trait measures when entered into the regression model simultaneously. Second, the interaction term was significant in just over one-third of the models. Further analysis revealed that the negative mood induction tended to increase the effect of the correlation between Negative Mood and the negatively-valenced outcomes and a similar patterns of results occurred after the positive mood induction with Positive Mood and the positively-valenced outcomes. These results support a mood congruent effect, but only after a strong emotional induction. And although the mood states were the only significant predictors in the regression models, significant personality trait relations were still present in the bivariate correlations. The mood induction seems to have increased the effect of mood on emotional processing. For a recent study with similar results see Rafienia, Azadfallah, Fathi-Ashtiani, and Rasoulzadeh-Tabatabaiei (2008).

Support for the trait congruency hypothesis has also been found using the personality system derived from the Reward Sensitivity Theory. Gomez and his colleagues (A. Gomez & Gomez, 2002; R. Gomez et al., 2004) used measures developed based on the Reward Sensitivity Theory to predict biases in emotional processes using the same or similar tasks used by Rusting (1999). In the first study, 163 students completed the State-Trait Anxiety Inventory (trait only), the Impulsivity items from the Eysenck Personality Inventory, the BIS/BAS Scales, and the Positive and Negative Affect Schedule (PANAS-mood; A. Gomez & Gomez, 2002). Students also completed three emotional information processing tasks. In the first task, students filled in missing letters of words with 15 resulting either in a positively- or neutrally-valenced word and 15 resulting in a negatively- or neutrally-valenced word. In the second task, the students were asked to determine whether 60 words (20 positive words, 20 negative words, and 20 neutral words) were positive, negative, or neutral, and a score was computed based on the number of correct responses. Students were given four minutes in the third task to recall as many words from the second task as possible. Consistent with predictions, Impulsivity and BAS sensitivity were significantly and positively correlated with constructing positively valenced-words on the first task, identifying positively-valenced words in the second task, and recalling positively-valenced words in the third task. Similarly, Anxiety and BIS sensitivity were correlated with the negatively-valenced outcomes of all three tasks. These correlations remained significant after partialing out positive and negative mood from the PANAS. From the PANAS, the only significant correlation was between negative mood and recognizing negatively-valenced words on the second task.

In a follow-up study (R. Gomez et al., 2004), 132 students completed the State-Trait Anxiety Inventory (trait only), a functional impulsivity scale, and the Generalized Reward and Punishment Expectancy Scales. As before, students completed three emotional processing tasks. In the first task, students rated the pleasantness of pleasant, neutral, and unpleasant words. In the second task, students were asked to recall as many of the words from the second task as they could in three minutes. And students were asked to write a short story based on an emotionally ambiguous statement in the third task. The emotional valence of the story written by the participants was rated as positive, neutral, or negative.

Anxiety and Punishment Expectancy were significantly positively correlated with rating words as more unpleasant, recalling more unpleasant words, and writing an unpleasant story, and negatively and significantly correlated with the pleasantly-valenced outcomes of each task. Impulsivity and Reward Expectancy were significantly correlated with all of the outcomes in the expected directions, except that there was not a significant correlation with the ratings of the unpleasant words. There were no significant correlations with any of the neutrally-valenced outcomes. In a series of regressions, one with Impulsivity and Anxiety and the other with Positive Expectancy and Negative Expectancy, Impulsivity and Positive Expectancy were significantly correlated with the pleasantly-valenced outcomes and Anxiety and Negative Expectancy were significantly correlated with the unpleasantly-valenced outcomes for the word pleasantness rating task and the word recall task. For the story completion task, both predictors in each model were correlated with both the pleasantly- and unpleasantly-valence outcomes.

To examine the joint subsystem hypothesis, an interaction term (e.g., Impulsivity × Anxiety) was added in a second step to the regression equations. The interaction term was not significant for any of the outcomes and the increase in the amount of variance accounted for by the model was also never significant. However, Gomez et al. (2004) interpreted the results from the first step of the story completion task regressions as supporting the joint subsystems hypothesis as both the positively- and negatively-toned predictors were significant in both models for the pleasant and unpleasantly-valenced outcomes. This finding may have resulted from the emotionally unclear statements activating both the BIS and the BAS, and the greater complexity and ambiguity of the task in comparison to the first two tasks.

Noguchi, Gohm, and Dalsky (2006) further examined tendencies of individuals to focus on either positive or negative information by constructing the Attention to Positive and Negative Information Scale (APNI). Items were written to capture cognitive processes including attending to, thinking about, and recalling positive or negative events. The scale includes an attention to positive information subscale (API, "No matter who is smiling, I notice that happy face.") and an attention to negative information subscale (ANI, "I noticed when something is not going well even if it's a trivial thing.").

In the first study, 201 students completed the experimental version of the APNI as well as the BIS/BAS Scales. BIS sensitivity was significantly correlated with ANI (r = .22), and API was significantly correlated with both BAS-Reward Sensitivity (r = .32) and BAS-Fun Seeking (r = .21). None of the other subscales were intercorrelated.

In a later study with the final version of APNI, 198 students also completed the BIS/BAS Scales and were asked to determine how happy and sad a character appeared in a story (Noguchi et al., 2006). In the story, the character undergoes a counseling session and recalls ten happy and ten sad events from his life. Both API-R (revised) and BAS sensitivity (a composite of all three subscales) predicted perceiving the character as a happy person (both r = .18). However, ANI-R was not positively correlated with perceiving the character as sad, and was instead positively correlated with perceiving the character as happy (r = .25), which does not support the construct validity of this subscale. However, BIS sensitivity was positively correlated with perceiving the character as sad.

There are studies that support the trait congruency hypotheses both in terms of studies designed specifically to examine the Reward Sensitivity Theory and other studies with related designs. In terms of the Reward Sensitivity Theory, for simple tasks BAS sensitivity was associated with a bias toward processing positively-valenced emotional stimuli and BIS sensitivity was associated with a bias toward processing negatively-valenced emotional stimuli. With more complex tasks, BAS sensitivity was also negatively associated with a bias toward processing negatively-valenced emotional stimuli and BIS sensitivity with a bias toward processing positively-valenced emotional stimuli supporting a joint effect. This bias in processing associated with the BIS and the

BAS can be extended to examine and predict how students perceive and rate features of a course depending on the emotional valence of the features of the course. A pilot study was conducted to determine the emotional valence of features of a course that could be used to design the main study.

CHAPTER 2

PILOT STUDY

A pilot study was conducted to help establish the design of aspects of the course descriptions that were used in the main study. The BIS/BAS Scales and GRAPES were administered to assess BIS and BAS functioning as well as seven personality scales from the International Personality Item Pool (IPIP). Interest ratings were obtained on 32 courses (e.g., Introduction to Anthropology, Drawing) to determine which courses were of similar, general interest among students. To establish the positive and negative features of a course, the questionnaire asked students to list five course features that would make them more likely to enroll in a class and five course features that would make them less likely to enroll in a class. In addition, students were asked to rate their level of preference for having specific course features (e.g., strict attendance policy vs. attendance optional, group projects vs. individual projects) in a course. The correlations of BIS and BAS sensitivity with ratings of interest in course features were used to determine the course features less highly preferred by students with a higher BIS sensitivity and more highly preferred by students with a higher BAS sensitivity. The results of the pilot study were used to develop the design of the course descriptions presented in the main study.

CHAPTER 3

PILOT STUDY: METHOD

Participants

The sample consisted of 112 students from the Georgia Institute of Technology Psychology research participant pool. One participant was removed from analysis as some of the responses were outliers and nonsensical (e.g., extremely high preference for an inconvenient course time) resulting in a sample size of 111 participants. Participants were required to be an undergraduate student of at least 18 years of age. The sample consisted of both females (41%) and males (59%) with an average age of 20.2 years (SD = 1.55). The ethnic distribution was 64 percent White, 19 percent Asian or Pacific Islander, 8 percent African American, 7 percent Hispanic, and 2 percent selected the other category (e.g., multiracial). Participants were given one hour of study credit in exchange for participation.

Measures

Demographic and background questions. Participants were asked to provide their names, genders, date of births, and races/ethnicities.

Personality questionnaire. The five 20-item scales from the IPIP written to assess the five dimensions from the five factor model were included (Goldberg et al., 2006). Agreeableness assesses a tendency to be cooperative rather than antagonistic. Conscientiousness assesses a tendency to act dutifully and in an achievement-oriented manner rather than acting spontaneously. Extraversion assesses a tendency to be in high spirits and seek out the company of others rather than acting alone or working in isolation. Neuroticism assesses a tendency to experience negative emotions (e.g., anxiety, depression). Openness (also referred to as Openness to Experience) assesses a tendency to seek a variety of experiences and an appreciation of art, exotic foods, and unusual ideas. In addition, a ten-item anxiety scale and a nine-item enthusiasm scale from the IPIP were included to examine personality correlates that appeared similar to BIS and BAS functioning, respectively. Respondents indicated how accurately each statement described them on a 5-point scale (1 = very inaccurate, 5 = very accurate).

BIS/BAS functioning. Carver and White's (1994) BIS/BAS Scales and Ball and Zuckerman's (1990) Generalized Reward and Punishment Expectancy Scales (GRAPES) were used to assess BIS and BAS functioning. The 20-item BIS/BAS Scales include one BIS scale and three BAS scales assessing drive, fun, and reward responsiveness. A 6-point scale was used with which participants indicated their level of agreement with each statement (1 = strongly disagree, 6 = strongly agree). The 30-item GRAPES consists of two scales measuring Reward Expectancy and Punishment Expectancy. Respondents indicated whether or not they agreed with each statement (yes, no).

Course interest ratings. Participants were asked to rate their level of interest in 32 courses. Courses were taken from the Georgia Tech Course Catalog (see Georgia Institute of Technology, n.d.) as well as from course listings from other schools that were available online (see e.g., Indiana Wesleyan University, n.d.; University of Minnesota, n.d.). Each rating item provided the title of the course and a brief description of the course content. Participants rated each course on a 7-point scale (1 = extremely uninterested, 7 = extremely interested).

Course feature preferences. Two methods were used to obtain the features of a course that participants preferred. First, participants were asked to provide five features of a course that would make them more likely to enroll in a class and five features of a course that would make them less likely to enroll in a class by completing a sentence (e.g., “I would be more likely to enroll in a class if ________”). Second, participants were asked to provide ratings of their preferences between two opposing course features (e.g., strict attendance policy/attendance optional, no reading assignments/heavy reading load). Participants rated each of the 45 course feature items on a 7-point scale with each term appearing on either end and “neutral” appearing in the middle (e.g., 1 = strict attendance policy, 4 = neutral, 7 = attendance optional).

Procedure

Upon arrival to the study session, participants were given a consent form to review and sign, and the experimenter read an introductory script. Next, participants were administered the questionnaire and instructed to turn it in to the experimenter upon completion.

CHAPTER 4

PILOT STUDY: RESULTS/DISCUSSION

Table 1 displays the descriptive statistics and intercorrelation among study variables. The following demarcations were used to report the internal consistency of the study variables: excellent (α is .90 or greater), good (α is between .80 and .89), fair (α is between .70 and .79), and unacceptable (α less than .70; Cicchetti, 1994). The internal consistencies were unacceptable to fair for the BIS/BAS Scales (α ranged from .66 to .74), unacceptable for GRAPES (α = .65 and .68), and good to excellent for the five factor model IPIP factors (α ranged from .86 to .94). The internal consistencies were good and fair for Anxiety (α = .85) and Enthusiasm (α = .72), respectively.

However, α < .70 will not be used as a cut of for excluding variables in later analyses. The internal consistency reliability of a scale confounds reliability and the heterogeneity of the items included in the scale, and is a function of the number of items included in the scale (Ackerman & Humphreys, 1991). Moreover, within a fixed period of time to administer a questionnaire, the developer of the questionnaire may seek to emphasize the accuracy or exactness of the concept(s) assessed (i.e., fidelity) or the breadth of the concept(s) assessed (i.e., bandwidth; Cronbach, 1990). An emphasis toward one dimension will de-emphasize the other dimension. The decision of which dimension to emphasize must be made by the questionnaire developer based on the purpose of the assessment and the concept(s) assessed. In terms of a single scale, a focus on fidelity results in a scale with a higher internal consistency reliability yet less breadth. Conversely, a focus on bandwidth results in a scale with more breadth and a lower internal consistency reliability. As Punishment Expectancy and Reward Expectancy assess broadly defined constructs (i.e., BIS and BAS sensitivity), a lower internal consistency reliability estimate may not be indicative of a lower reliability—just greater item heterogeneity. On the other hand, the BAS scales assess more narrowly defined concepts. The lower reliability estimates are most likely due to the small number of items included in each BAS scale.

In general, the pattern of correlations confirmed expectations. Although a positively-toned trait may have correlated with a negatively-toned trait, the direction of the effect was negative, which is consistent with past research (Torrubia et al., 2001). The main departures were the high positive correlation between BIS and BAS-Reward Responsiveness (r = .39), the nonsignificant correlation between BAS-Reward Responsiveness and Positive Expectancy (r = .08), and the nonsignificant correlation between Enthusiasm and BAS-Reward Responsiveness (r = .08). Consistent with past findings (e.g., Diefendorff & Mehta, 2007; Smillie & Jackson, 2005; Smits & Boeck, 2006), these results bring into question the construct validity of the BAS-Reward Responsiveness scale. Otherwise, the construct validity of the measures was supported in terms of convergent validity. In addition, the extremely high correlation between

Table 1. Study Variable Descriptive Statistics and Correlations

	M	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. BIS	4.29	0.67	.73													
2. BAS–Full	4.49	0.50	0.11	.78												
3. BAS–Fun	4.28	0.86	-0.14	0.82*	.73											
4. BAS–RR	4.96	0.51	0.39*	0.69*	0.36*	.66										
5. BAS–Drive	4.11	0.69	0.07	0.71*	0.36*	0.27*	.74									
6. PE	0.60	0.19	0.32*	-0.08	-0.27*	0.06	0.08	.68								
7. RE	0.51	0.20	-0.39*	0.41*	0.40*	0.08	0.41*	-0.29*	.65							
8. Neuroticism	2.52	0.64	0.53*	-0.15	-0.31*	0.11	-0.08	0.59*	-0.49*	.90						
9. Extraversion	3.40	0.72	-0.12	0.48*	0.44*	0.24*	0.35*	-0.31*	0.52*	-0.28*	.94					
10. Agreeableness	3.59	0.52	0.11	0.12	0.14	0.11	0.00	-0.41*	0.08	-0.33*	0.18	.86				
11. Conscientiousness	3.58	0.56	-0.07	0.00	-0.11	-0.11	0.25*	0.05	0.23*	-0.15	0.05	0.20*	.90			
12. Openness	3.58	0.58	-0.19*	0.24*	0.16	0.19*	0.19	0.05	0.31*	-0.12	0.14	0.03	0.20*	.86		
13. Anxiety	2.82	0.75	0.66*	-0.10	-0.29*	0.18	-0.04	0.49*	-0.39*	0.89*	-0.18	-0.14	-0.12	-0.09	.85	
14. Enthusiasm	3.51	0.58	-0.19	0.30*	0.25*	0.08	0.33*	-0.31*	0.44*	-0.33*	0.52*	0.39*	0.50*	0.25*	-0.19*	.72

Note. Internal consistency reliabilities along the diagonal. BAS-RR = BAS Reward Responsiveness, RE = Reward Expectancy, and PE = Punishment Expectancy.
*$p < .05$.

Neuroticism and Anxiety (r = .89) suggests that these two traits are essentially assessing the same personality construct (after correcting for unreliability in the measures $\hat{\rho}$ = 1.0).

Past research has found that students tend to give higher ratings of teaching to humanities and art courses, followed by courses in the social sciences, then courses in the natural sciences (Beran & Violato, 2005; Cashin, 1995). Mathematics courses typically received the lowest ratings. A factor analysis was computed to determine the factor structure of the courses included in the study (see Table 2). Principal axis factoring was used with direct oblimin rotation. The scree plot supported a four-factor solution with social sciences, fine arts, humanities, and economics/business/public policy courses loading onto separate factors. The results of the factor analysis were used to combined courses into rating groups that did not load onto the same factor in an attempt to minimize the effect the title and description of a course may have had on participants' ratings.

In contrast to past findings, the results revealed that the social science courses were rated the highest, fine arts courses tended to appear in the middle, humanities courses and courses that focused on writing (e.g., Creative Writing, Script Writing) appeared lowest, and economic/business/public policy courses appeared throughout (see Table 3). The course feature ratings of participants high on the negatively-toned traits may be interpreted in terms of a preference for remaining anonymous and a grade focus (see Table 4). The results of the average ratings of the courses and the variance of the ratings were used to determine courses of similar interest among students for the main study. Course features with a significant correlation (an effect size of .19 or higher) were considered for use in the main study. Scores on the negatively-toned traits were related

Table 2. Course Factor Analysis Structure

	1	2	3	4
Humanities: World Civilization	**0.55**	0.09	0.03	**0.51**
Introduction to Anthropology	**0.49**	-0.23	-0.29	-0.13
Religions of the World	**0.46**	-0.01	-0.09	0.04
American Popular Arts and Public Life, 1940 to present	**0.45**	-0.12	-0.26	0.06
Exploring the Universe	**0.42**	-0.08	0.20	-0.11
History of Art	**0.41**	-0.36	-0.03	0.18
Principles of Human Anatomy	**0.38**	-0.10	-0.15	-0.26
History of Architecture I	**0.37**	-0.26	0.02	0.13
Script Writing	-0.13	**-0.73**	-0.12	0.14
Drawing	-0.04	**-0.70**	0.03	-0.09
Time Arts: 2-D Animation	-0.17	**-0.69**	0.24	-0.09
Introduction of Photography	0.13	**-0.61**	0.02	-0.10
Creative Writing	0.03	**-0.53**	-0.32	0.00
Introduction to Film	0.21	**-0.53**	0.01	-0.07
Fundamentals of Music Theory	0.16	**-0.43**	-0.01	-0.18
Introduction to Language I	0.21	-0.27	-0.23	0.00
Introduction to Philosophy	0.11	-0.17	-0.05	0.16
Psychology of Personality	-0.25	-0.10	**-0.90**	0.06
Introduction of Abnormal Psychology	0.10	-0.03	**-0.73**	-0.08
General Psychology	-0.01	-0.14	**-0.65**	-0.09
Introduction to Sociology	-0.07	0.00	**-0.62**	**0.31**
Families and Culture: Alcohol and Drugs	0.10	0.14	**-0.54**	-0.17
Criminology	0.03	0.07	**-0.53**	-0.08
American Mass Media	0.16	-0.13	**-0.30**	0.17
Nutrition and Health	0.09	0.23	-0.26	-0.11
Citizens, Consumers, and Corporations	0.05	-0.04	0.02	**0.69**
The Global Economy	-0.05	0.00	0.07	**0.68**
Foundation-Public Policy	0.23	0.22	-0.16	**0.61**
Entrepreneurship	-0.17	0.04	0.08	**0.60**
Tourism Development: Principles, Processes, and Policies	0.25	0.03	0.06	0.26

Note. Values ≥ .30 placed in boldface.

Table 3. Average Level of Interest in Courses

Course Title	Mean	SD
Psychology of Personality	5.29	1.30
General Psychology	5.26	1.20
Criminology	4.86	1.42
Introduction of Abnormal Psychology	4.86	1.49
Entrepreneurship	4.80	1.70
Introduction of Photography	4.62	1.81
Introduction to Philosophy	4.59	1.75
Introduction to Sociology	4.58	1.39
Religions of the World	4.55	1.87
Exploring the Universe	4.54	1.70
Introduction to Film	4.42	1.73
Principles of Human Anatomy	4.29	1.64
Introduction to Anthropology	4.27	1.68
Fundamentals of Music Theory	4.10	1.88
The Global Economy	4.03	1.71
Nutrition and Health	3.99	1.69
Western/American Intellectual and Social History	3.98	1.70
American Mass Media	3.95	1.66
Tourism Development: Principles, Processes, and Policies	3.95	1.66
Time Arts: 2-D Animation	3.95	1.76
Families and Culture: Alcohol and Drugs	3.89	1.73
Drawing	3.86	2.00
Introduction to Archaeology	3.83	1.65
American Popular Arts and Public Life, 1940 to present	3.79	1.58
Humanities: World Civilization	3.78	1.56
Creative Writing	3.58	1.88
Citizens, Consumers, and Corporations	3.57	1.56
Introduction to Language I	3.41	1.66
Foundation-Public Policy	3.40	1.52
History of Architecture I	3.35	1.59
History of Art	3.18	1.65
Script Writing	3.03	1.73

Table 4. Correlation between Course Feature Ratings and Negatively-Toned Traits

Course Feature	BIS	PE	N	Anxiety
Instructor stays on topic/Instructor often strays from topic	**-0.36***	**-0.23***	**-0.28***	**-0.30***
Intellectually demanding/Intellectually simple	**0.34***	0.11	**0.22***	0.18
Highly theoretical/Highly practical/applied	**0.33***	0.03	0.05	0.13
Tests require verbatim recall/Tests require demonstration of understanding	**-0.30***	**-0.20***	**-0.29***	**-0.41***
Small class size/Large class size	**0.27***	0.17	0.16	0.18
Challenging/Straightforward	**0.25***	**0.22***	0.15	0.16
Cumulative exams/Exams are not cumulative	**0.23***	-0.09	-0.02	0.03
Convenient class time/Inconvenient class time	**-0.23***	0.07	0.15	0.10
In-class presentations required/No in-class presentations	**0.21***	0.13	0.10	0.11
Afternoon class/Evening class	**-0.21***	0.18	0.09	0.02
Submissive Instructor/Domineering Instructor	**-0.20***	**-0.30***	**-0.21***	-0.15
Relevant to major/Irrelevant to major	**-0.20***	**-0.22***	-0.16	-0.10
Encourages discussion/Focuses on lecture	**0.20***	0.13	0.15	0.13
Calls on students/Rarely calls on students	**0.19***	0.04	0.07	0.07
Intense/Dull	0.19	0.17	0.12	0.17
Tests returned quickly/Tests returned slowly	-0.16	-0.15	**-0.22***	-0.17
No reading assignments/Heavy reading load	-0.16	-0.09	-0.07	-0.04
Morning Class/Afternoon class	-0.14	0.04	-0.02	-0.08
Humorous Instructor/Humorless Instructor	-0.14	**0.19***	0.08	-0.09
Includes class time on Friday/No Friday class time	0.14	-0.02	0.14	0.17
Group Projects/Individual projects	0.12	-0.08	-0.05	0.00
Morning class/Evening class	-0.10	0.10	0.06	0.01
Light homework load/Heavy homework load	-0.10	-0.14	-0.07	-0.08
High potential to learning/Low potential for learning	0.10	-0.05	0.18	0.17
Boring Instructor/Interesting Instructor	0.10	-0.07	-0.14	-0.06
Exciting/Tedious	0.09	0.14	0.07	0.04
Instructor interested in students learning/Instructor interested in students grade	0.09	0.09	0.12	0.14
Easy/Difficult	-0.08	-0.14	-0.05	-0.07
Slow pace/Fast pace	-0.07	-0.08	-0.07	-0.06
Light workload/Heavy workload	-0.07	-0.08	-0.05	-0.07
Boring/Interesting	0.06	-0.08	-0.16	-0.09
Strict test make-up policy/Lenient test make-up policy	-0.06	0.02	-0.04	-0.02
Many opportunities for extra credit/No opportunities for extra credit	-0.06	-0.13	**-0.22***	**-0.23***
Strict attendance policy/Attendance optional	-0.05	0.06	-0.01	-0.11
Emphasis on lecture/Emphasis on reading assignments	-0.05	0.05	0.08	0.11
Strict grader/Lenient grader	0.05	0.18	0.05	0.04
Pop quizzes every class/No pop quizzes	-0.04	0.03	-0.09	-0.07
Grade based on tests/Grade based on group projects	-0.04	0.01	-0.09	-0.03
Multiple choice exams/Essay exams	0.03	-0.03	0.00	0.05
Unknown instructor/Famous instructor	0.03	0.04	0.01	-0.01
Strict late policy/No late policy	0.02	0.15	-0.01	-0.01

Table 4 (continued).

	BIS	PE	N	Anxiety
Grade based on papers/Grade based on tests	0.02	0.04	0.13	0.02
Narrow Focus/Broad Focus	0.02	-0.06	-0.09	-0.07
Stimulating/Repetitive	-0.02	0.10	0.10	0.04
Self-confident instructor/Timid instructor	-0.01	**0.22***	**0.25***	0.18

Note. PE = Punishment Expectancy, N = Neuroticism.
**p* < .05 and in boldface.

to a preference for a humorless, timid, submissive instructor who stays on topic, rarely calls on students, and returns tests quickly. The negatively-toned traits were also associated with a preference for large classes that are intellectually simple, straightforward, and do not require in-class presentations. In addition, the negatively-toned traits were also related to a preference to exams that require verbatim recall instead of a demonstration of understanding the material and to exams that are not cumulative. As described earlier, the trait congruent processing approach, Reward Sensitivity Theory, and past research support the conclusion that those who score more highly on negatively-toned traits will notice and rate courses with negative features more negatively than those who score lower on negatively-toned traits. The results from this study have identified course features that are associated with negatively-toned traits and were used to create course descriptions with hypothetical comments that those with a higher standing on BIS sensitivity would find more aversive than individuals with a lower standing on BIS sensitivity.

The pattern of correlations between the positively-toned traits and the course feature ratings was consistent with a preference for in-class interaction and a learning value focus (see Table 5). Scores on the positively-toned traits were associated with a preference for an instructor who is humorous, self-confident, interesting, domineering, interested in students' learning, calls on students, and encourages in-class discussions.

Table 5. Correlation between Course Feature Ratings and Positively-Toned Traits

	BAS (Full)	BAS (Fun)	BAS (Drive)	BAS (RR)	RE	E	Enth.
Self-confident instructor/Timid instructor	**-0.42***	**-0.34***	**-0.30***	**-0.29***	**-0.22***	**-0.29***	-0.17
Boring Instructor/Interesting Instructor	**0.26***	0.13	**0.20***	**0.27***	0.13	0.10	0.04
Stimulating/Repetitive	**-0.25***	-0.18	-0.08	**-0.31***	-0.07	-0.05	**-0.19***
Strict late policy/No late policy	**0.25***	**0.25***	0.13	0.15	0.01	0.05	**-0.21***
Intense/Dull	**-0.23***	**-0.30***	-0.06	-0.12	-0.14	-0.11	-0.10
Convenient class time/Inconvenient class time	**-0.22***	-0.12	-0.11	**-0.29***	-0.01	-0.17	-0.02
Exciting/Tedious	**-0.20***	**-0.26***	-0.09	-0.06	-0.07	-0.04	-0.08
Humorous Instructor/Humorless Instructor	**-0.20***	**-0.21***	-0.06	-0.16	0.00	**-0.22***	-0.16
Grade based on tests/Grade based on group projects	**0.20***	**0.20***	0.18	0.03	0.08	0.16	0.17
Highly theoretical/highly practical/applied	**0.19***	0.06	0.14	**0.26***	-0.10	0.04	0.12
Boring/Interesting	0.18	0.12	0.15	0.15	0.17	0.08	0.11
Calls on students/Rarely calls on students	-0.17	**-0.20***	-0.05	-0.11	**-0.21***	**-0.21***	-0.17
Tests returned quickly/Tests returned slowly	0.17	0.15	**0.21***	0.00	0.15	0.07	0.16
In-class presentations required/No in-class presentations	-0.16	**-0.20***	-0.08	-0.05	**-0.29***	**-0.30***	**-0.33***
Encourages discussion/Focuses on lecture	-0.15	-0.17	-0.15	0.01	**-0.29***	**-0.25***	**-0.24***
Strict test make-up policy/Lenient test make-up policy	0.14	0.18	0.10	0.01	0.09	0.18	-0.09
Instructor interested in students learning/Instructor interested in students grade	-0.14	**-0.23***	-0.01	-0.04	-0.11	0.09	-0.17
Small class size/Large class size	-0.14	-0.17	-0.06	-0.06	-0.13	-0.09	-0.16
Tests require verbatim recall/Tests require demonstration of understanding	0.14	**0.24***	0.11	-0.09	**0.23***	0.08	0.07
Intellectually demanding/Intellectually simple	-0.13	-0.15	-0.13	0.02	**-0.33***	**-0.20***	**-0.32***
Grade based on papers/Grade based on tests	-0.11	-0.05	-0.13	-0.09	-0.08	-0.15	**-0.20***
Light homework load/Heavy homework load	0.11	0.09	0.12	0.04	**0.22***	0.08	**0.19***
Cumulative exams/Exams are not cumulative	0.11	0.03	0.02	**0.22***	-0.07	0.08	-0.12
Pop quizzes every class/No pop quizzes	-0.10	-0.03	-0.03	-0.18	0.07	-0.10	-0.11
Unknown instructor/Famous instructor	0.09	-0.04	0.13	0.14	0.02	0.03	-0.03
Submissive Instructor/Domineering Instructor	0.09	**0.24***	-0.05	-0.05	**0.35***	**0.21***	**0.27***
Morning Class/Afternoon class	0.09	0.17	0.03	-0.04	0.07	-0.05	**-0.29***
Emphasis on lecture/Emphasis on reading assignments	0.08	-0.01	0.13	0.09	0.12	0.10	0.16
Strict attendance policy/Attendance optional	0.08	0.14	-0.03	0.06	0.04	-0.02	**-0.28***
High potential to learning/Low potential for learning	-0.08	-0.06	-0.12	-0.01	-0.16	-0.04	-0.01
Group Projects/Individual projects	-0.08	**-0.24***	0.00	0.11	-0.05	-0.11	-0.02
Morning class/Evening class	0.07	0.19	0.03	-0.09	0.07	-0.07	**-0.31***
Challenging/Straightforward	-0.07	**-0.22***	0.03	0.08	**-0.28***	-0.18	**-0.20***
Light workload/Heavy workload	-0.05	-0.03	-0.09	0.00	0.06	0.01	**0.22***
Includes class time on Friday/No Friday class time	-0.05	-0.05	-0.10	0.05	-0.02	0.12	-0.03

Table 5 (continued).

	BAS (Full)	BAS (Fun)	BAS (Drive)	BAS (RR)	RE	E	Enth.
Afternoon class/Evening class	-0.05	0.04	0.00	-0.17	0.09	-0.14	-0.07
Many opportunities for extra credit/No opportunities for extra credit	-0.04	0.02	-0.02	-0.11	0.08	-0.07	**0.23***
Strict grader/Lenient grader	-0.04	-0.12	0.04	0.02	0.04	0.13	-0.15
Easy/Difficult	0.04	0.07	0.03	-0.04	**0.19***	-0.02	**0.22***
Narrow Focus/Broad Focus	-0.02	-0.07	0.01	0.02	0.04	-0.01	0.10
Instructor stays on topic/Instructor often strays from topic	-0.02	0.18	0.03	**-0.33***	**0.27***	0.00	-0.06
Slow pace/Fast pace	0.02	0.08	-0.03	-0.02	0.14	0.18	**0.26***
Multiple choice exams/Essay exams	0.02	-0.01	0.06	0.00	-0.02	0.04	0.17
No reading assignments/Heavy reading load	-0.02	-0.07	0.03	0.01	0.11	0.00	**0.33***
Relevant to major/Irrelevant to major	-0.02	0.10	-0.08	-0.09	0.14	0.03	0.02

Note. BAS–RR = BAS Reward Responsiveness, RE = Reward Expectancy, E = Extraversion, Enth. = Enthusiasm.
*$p < .05$ and in boldface.

The positively-toned traits were also associated with a preference for an exciting, intense, challenging, stimulating, intellectually demanding course that requires in-class presentations and group projects. In addition, the positively-toned traits were associated with a preference for exams that require a demonstration of understanding rather than verbatim recall. The results from Table 5 were also used to create course descriptions with hypothetical comments that those with a higher standing on BAS sensitivity would find more rewarding than individuals with a lower standing on BAS sensitivity. The course features that were not significantly correlated with either the negatively-toned or positively-toned traits were used to create neutral comments. The free response course feature questions did not yield any course features that were not already captured by the 45 course feature items.

CHAPTER 5

MAIN STUDY

The main study extended the use of the trait congruency hypothesis and the Reward Sensitivity Theory to the examination of how undergraduate college students attend to and perceive course selection information. Undergraduate students were asked to review and rate course descriptions. Questionnaires were administered to provide a broad assessment of personality and to assess BIS and BAS sensitivity to investigate their association with course selection preferences. Based on effect sizes observed in past research (Gomez & Gomez, 2002; Gomez et al., 2004; Rusting, 1999), a power analysis was computed to determine the sample size necessary to determine whether a correlation was significantly different from zero with an effect size of .20, an alpha of .05, and power of .80. The power analysis was conducted for a two-tailed test. The analysis yielded a target sample size of at least 193 participants.

As in the pilot study, the five 20-item scales from the International Personality Item Pool (IPIP) designed to assess the five dimensions from the five factor model including Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness were administered (Goldberg et al., 2006). The IPIP scales provide a broad assessment of personality and enable a comparison between the factor space of the five factor model and the other study variables. Neuroticism and Extraversion were associated with BIS and BAS sensitivity as described earlier (Gray et al., 1983; Pickering & Gray, 1999; Torrubia et al., 2001). Their inclusion allows for an examination of the extent to which Neuroticism and Extraversion, as assessed by the 20-item IPIP scales, correlate with BIS sensitivity and BAS sensitivity, respectively.

BIS and BAS functioning were assessed with the BIS/BAS Scales and the Generalized Reward and Punishment Expectancy Scales (GRAPES, Ball & Zuckerman, 1990; Carver & White, 1994). Both scales were specifically designed to assess BIS and BAS sensitivity based on Gray's Reward Sensitivity Theory. The items of the BIS/BAS Scales were written to capture the overall conceptualization and theory of BIS and BAS functioning (Carver & White, 1994). BIS items were intended to reflect a concern for and sensitivity to the occurrence of negative events. A broader approach was taken to capture BAS functioning as this aspect of Gray's (1987, 1994; Gray et al., 1983; Pickering et al., 1995; Pickering & Gray, 1999) theory was less well defined in comparison to BIS functioning. The BAS items were written to assess tendencies to pursue appetitive goals and potentially rewarding experiences, to act quickly in pursuing a desired outcome, and to respond positively after experiencing a reward. To address the low reliabilities found with the BIS/BAS Scales in the pilot study, additional items were taken from existing measures and written to underlie each of the four scales as described in the Method section for the main study.

GRAPES was selected for the study to provide a second assessment of BIS and BAS functioning. GRAPES was designed to capture expectations of either rewards or punishment from life events and includes two scales (Ball & Zuckerman, 1990). The Reward Expectancy scale measures the extent of an individual's optimistic expectations of success and satisfaction with life. In contrast, the Punishment Expectancy scale measures the extent of an individual's pessimistic expectations such as being a victim of a crime, contracting a major illness, or being involved in an accident. The inclusion of GRAPES enabled an examination of convergent validity with the BIS/BAS Scales.

Likert-type response scales were used instead of the original yes/no format in an attempt to increase the low reliabilities of the two scales observed in the pilot study.

Two other scales designed to assess aspects of Gray's Reward Sensitivity Theory were also considered, but deemed inappropriate for the study. Torrubia et al. (2001) expanded Torrubia and Tobena's (1984) Susceptibility to Punishment scale to the Sensitivity to Punishment and Sensitivity to Reward Questionnaire (SPSRQ). Although the SPSRQ has shown some promising results in terms of construct validity, a number of the questions were found to be potentially problematic or inappropriate when administered to college students (e.g., Do you often refrain from doing something because you are afraid of it being illegal?, Would it be difficult to ask your boss for a raise?). In addition, Gray and his colleagues developed the Gray-Wilson Questionnaire to measure aspects of Reward Sensitivity Theory (Wilson et al., 1989; Wilson, Gray, & Barrett, 1990). However, results from their initial studies revealed weak psychometric properties and evidence that did not support the construct validity of some of the scales.

The effect sizes established by Cohen (1988, 1992) for a small (r = .1), medium (r = .3), and large effect (r = .5) of a correlation were used to demarcate observed effect sizes. Consistent with past theory and research (Gray et al., 1983; Pickering & Gray, 1999; Torrubia et al., 2001), a high, positive correlation (between r = .40 and .60) of BIS sensitivity with Neuroticism was expected. For BAS sensitivity, a high positive correlation (between r = .40 and .60) with Extraversion was expected. As there is limited empirical research and little guidance from theory, a hypothesis regarding the association of BIS and BAS sensitivity with Conscientiousness, Agreeableness, and Openness was not posited.

A study was found that examined the association of the BIS/BAS Scales with Conscientiousness, Agreeableness, and Openness across two samples using a structural equation modeling approach (Smits & Boeck, 2006). The results indicated that Conscientiousness was significantly negatively associated with BAS-Fun (standardized parameter estimates = -.21 and -.23) in both samples and significantly positively associated with BAS-Drive (standardized parameter estimate = .27) and BAS—Reward Responsiveness (standardized parameter estimate = .18) in the first sample. Agreeableness was significantly positively associated with the BIS scale (standardized parameter estimates = .21 and .31) and significantly negatively associated with BAS-Drive (standardized parameter estimates = -.22 and -.28) in both samples and significantly positively associated with BAS-Reward Responsiveness (standardized parameter estimate = .21) in the first sample. Openness was significantly negatively associated with BIS (standardized parameter estimates = -.22) in the first sample and significantly positively associated with BIS-Fun (standardized parameter estimate = .26) in the second sample. Another study found that BAS sensitivity was only significantly correlated with Conscientiousness ($r_{BAS\text{-}Drive}$ = .49, $r_{BAS\text{-}Reward\ Responsiveness}$ = .40) and not significantly correlated with Openness or Agreeableness (Jackson & Smillie, 2004). In summary, the results supporting the association of the BIS/BAS Scales with Agreeableness, Conscientiousness, and Openness were inconsistent.

Hypothesis 1a. The BIS scale and Punishment Expectancy will be significantly positively correlated (between r = .40 and .60).

Hypothesis 1b. The BAS scales and Reward Expectancy will be significantly positively correlated (between r = .40 and .60).

Hypothesis 2a. The BIS scale and Punishment Expectancy will correlate significantly positively with Neuroticism (between r = .40 and .60).

Hypothesis 2b. The BAS scales and Reward Expectancy will correlate significantly positively with Extraversion (between r = .40 and .60).

To increase the ecological validity of the course information presented to participants, the course descriptions were presented in a form similar to popular websites used by undergraduates to select courses (e.g., Pick-A-Prof, n.d.; Rate My Professors, n.d.). Rate My Professors appears to be the most popular of the for profit, online student evaluation websites (Coladarci & Kornfield, 2007; Davison & Price, 2006; Kindred & Mohammed, 2005). In 2006, the website covered nearly 800,000 instructors across 6,000 colleges and universities in nine separate countries. Over eight million students were members, and the website averaged over 200,000 unique visitors per day. In a study with 216 college students, 92 percent said that they had heard of Rate My Professors, 80 percent had visited the website more than once, and 75 percent had used the website to decide whether to take a course (Davison & Price, 2006).

Table 6 displays the design scheme for the course rating task. The design scheme presents the patterns of valences for the comments and the use of the content (e.g., General Psychology, Criminology) for each course description. Each pattern of comment valences (e.g., 6 Appetitive, 0 Neutral, and 0 Aversive; 0 Appetitive, 6 Neutral, and 0 Aversive) was presented three times with different course content and different comments conforming to the pattern of valences. Across the patterns of valences, the same course content was repeated within group. For example, in the first group there were three patterns of valences and the content from three courses was used resulting in

(3 × 3) 9 course ratings. Six forms of the questionnaire were created to reduce the effect associated with a particular order of the questionnaire.

Table 6. Comment Valence Design Scheme

Group	Number of Courses	Number of Comments			Number of Course Ratings
		Appetitive	Neutral	Aversive	
		6	0	0	
1	3 Courses[1]	0	6	0	9 Course Ratings
		0	0	6	
		3	3	0	
2	3 Courses[1]	0	3	3	9 Course Ratings
		3	0	3	
		4	2	0	
		2	4	0	
3	3 Courses[1]	0	4	2	12 Course Ratings
		0	2	4	
4	3 Courses[1]	4	0	2	6 Course Ratings
		2	0	4	
Totals					
	12 Courses	24	24	24	36 Course Ratings

[1] Each course will have the same pattern of appetitive, neutral, and aversive comments, but with different comments.

The course descriptions were divided into groups to reduce an effect associated with the repeated use of course content. For example, the groupings ensure that participants do not see the same psychology course more than a maximum of 4 times if the psychology course were used as part of Group 3. In addition, the most meaningful contrasts among the different patterns of comment valences were placed into the same group to facilitate the design of planned comparisons and other analyses.

Participants' ratings of the course information were examined in three separate phases of analysis. First, the effect of task condition (i.e., the different patterns of valences of the course descriptions) on participants' ratings of the course descriptions was examined using planned comparisons. Second, the extent to which measures of BIS and BAS sensitivity predicted participants' ratings based on the pattern of comment valences was investigated by examining the correlations between participants' scores on the BIS/BAS measures and their ratings of a course description with specific patterns of comment valences. In addition, the interaction of BIS and BAS sensitivity was examined in a series of regressions (McClelland & Judd, 1993). And third, the effect of the comments' valences and the effect of the BIS/BAS measures was investigated simultaneously using a mixed-model procedure with the task condition (i.e., the pattern of course valences) of the course descriptions entered as Level 1 predictors and the BIS/BAS measures entered as Level 2 predictors.

Participants were expected to rate the course descriptions differently based on the pattern of comment valences. The examination of the effect of the task condition on participants' ratings of course descriptions provided a manipulation check to determine whether varying the emotional tone of the comments influenced participants' ratings. Several studies have reported a main effect based on the emotional valence of within-subjects factors (Byrne & Eysenck, 1995; Kverno, 2000; Quilty et al., 2007). One-way repeated measures ANOVA planned comparisons were used to determine the effect of task condition on participants' ratings of the course descriptions. Within each comment valence group (see Table 6), polynomial contrasts were computed to determine whether there was evidence of a linear or quadratic trend indicating that participants rated courses with more positive comments more highly than courses with less positive comments and courses with more negative comments more negatively than courses with less negative comments. The comment valence groups were designed to compare meaningful patterns of comment valences with each other, and enable an examination of whether a linear or quadratic trend was evident across course descriptions with different patterns in the variation of the number of positive and negative comments. The linear trend examined whether participants' ratings of the course descriptions decreased as the number of positive comments decreased and the number of negative comments increased. As the aversion associated with a negative comment may be greater than the appetitive nature of a positive comment, an analysis of a quadratic trend was also warranted. As the focus of the planned comparisons was on the examination of the levels of the within-subjects factor, the number of planned comparisons was limited based on the degrees of freedom associated with the within-subjects factor. The eight trend analyses required one degree of freedom each, using a total of eight degrees of freedom, which is less than the eleven degrees of freedom in a one-way repeated measures ANOVA for a within-subjects factor that has 12 levels. Similar to the expectations of the first two hypotheses, an effect size between a moderate and large effect (η^2 = .10) or greater was expected (cf. Cohen, 1988).

Hypothesis 3. Within each comment valence design scheme group, participants will rate course descriptions with more aversive comments lower than course descriptions with less aversive comments and course descriptions with more appetitive comments higher than course descriptions with less appetitive comments. An effect of η^2 = .10 or greater is expected.

As discussed in the Introduction section, Reward Sensitivity Theory (Gray, 1987, 1994; Gray et al., 1983; Pickering et al., 1995; Pickering & Gray, 1999) and past research (Gable et al., 2000; Larsen and Ketelaar, 1989, 1991) support the hypotheses that BIS sensitivity is associated with focusing on aversive stimuli and a tendency to perceive stimuli as aversive, and BAS sensitivity is associated with focusing on appetitive stimuli and a tendency to perceive stimuli as appetitive. A similar effect was observed in the pilot study with a significant negative correlation between BIS sensitivity and a preference for aversive course features (e.g., $r_{BIS\text{-}intellectually\ demanding} = -.34$, $r_{BIS\text{-}challenging} = -.25$) and a significant positive correlation between BAS sensitivity and a preference for appetitive course features (e.g., $r_{BAS\text{-}interesting\ instructor} = .26$, $r_{BAS\text{-}stimulating} = .25$). Reward Sensitivity Theory (Gray, 1987, 1994; Gray et al., 1983; Pickering et al., 1995; Pickering & Gray, 1999), past research (Gable et al., 2000; Larsen and Ketelaar, 1989, 1991), and the results from the pilot study support the prediction that BIS and BAS sensitivity influence participants' course description ratings. An approximately moderate effect size (between $r = .2$ and .4) for the correlation between BIS and BAS sensitivity and course description ratings was expected based on past research (e.g., Gomez, Cooper, McOrmond, Tatlow, 2004; Gomez & Gomez, 2002; Rusting, 1999) and the results from the pilot study.

Hypothesis 4a. Scores on the BIS scale and Punishment Expectancy will correlate negatively with ratings of course descriptions with aversive features (between $r = -.20$ and $-.40$).

Hypothesis 4b. Scores on the BAS scales and Reward Expectancy will correlate positively with ratings of course descriptions with appetitive features (between $r = .20$ and .40).

As some of the course descriptions presented both aversive and appetitive features, the course descriptions rapidly changed in terms of the number of aversive and appetitive features included in each course description, and the task was relatively unconstrained, the joint subsystems hypothesis as described by Corr (2001) was examined by testing for the presence of an interaction effect. The methods described by McClelland and Judd (1993) were used to test for interaction effects.

Hypothesis 5. The interaction of BIS sensitivity and BAS sensitivity will account for a significant amount of variance in ratings of course descriptions with aversive and appetitive features within models that include BIS and BAS sensitivity as main effects. As the amount of power associated with detecting an interaction effect is low (McClelland & Judd, 1993), any significant effect will be interpreted as support for this hypothesis. Higher levels of BAS sensitivity are expected to attenuate the influence of BIS sensitivity on ratings of course descriptions with aversive features, and higher levels of BIS sensitivity are expected to attenuate the influence of BAS sensitivity on ratings of course descriptions with appetitive features.

The effect of the comment valences and the BIS/BAS measures was investigated simultaneously using a mixed-model procedure with the different conditions of the course description rating task added as Level 1 predictors and the BIS/BAS measures added as Level 2 predictors. This analysis enabled a simultaneous examination of the effect of the task condition, the BIS/BAS measures, and their interaction on participants' ratings of the course descriptions. A similar interaction has been reported in past research as discussed earlier (Byrne & Eysenck, 1995; Kverno, 2000; Quilty et al., 2007). A separate set of mixed-model procedures were conducted for each comment valence group (see Table 6) to examine how the effect of the predictors varied across course descriptions with different patterns of positive and negative comments. Support for the hypotheses was judged based on whether the fit of at least a majority of the models was significantly improved, whether or not the improvement was the result of a fixed effect (versus a random effect) in a majority of the models with a significant improvement in fit, and the amount of reduction in Level 1 variance (σ^2) and Level 2 variance (τ_{00}). As Level 2 variables only affect Level 2 variance components (as opposed to the Level 1 variance components), it was expected that the amount of Level 2 variance would decrease by τ_{00} = .02 or greater with the addition of the Level 2 predictors. As cross-level interactions affect both Level 1 and Level 2 variance components, it was expected that the amount of Level 1 variance would decrease by σ^2 = .02 or greater and the amount of Level 2 variance would decrease by τ_{00} = .02 or greater with the addition of the cross-level interactions.

Hypothesis 6a. The main effect of BIS sensitivity will be significant in a model with course description condition included as a predictor. The addition of Level 2 predictors will also improve the fit of 50 percent or more of the models, and of those models, 50 percent or more will include a significant Level 2 fixed effect. In addition, the amount of Level 2 variance will decrease by τ_{00} = .02 or greater.

Hypothesis 6b. The main effect of BAS sensitivity will be significant in a model with course description condition included as a predictor. The addition of Level 2 predictors will also improve the fit of 50 percent or more of the models, and of those models, 50 percent or more will include a significant Level 2 fixed effect. In addition, the amount of Level 2 variance will decrease by τ_{00} = .02 or greater.

Hypothesis 6c. The interaction between the condition of the course descriptions and participants' standing on BIS sensitivity will be significant in a model with course description condition included as a predictor. The addition of the cross-level interactions will also improve the fit of 50 percent or more of the models, and of those models, 50 percent or more will include a significant cross-level interaction fixed effect. In addition, the amount of Level 1 variance will decrease by $\sigma^2 = .02$ or greater and the amount of Level 2 variance will decrease by $\tau_{00} = .02$ or greater.

Hypothesis 6d. The interaction between the condition of the course descriptions and participants' standing on BAS sensitivity will be significant in a model with course description condition included as a predictor. The addition of the cross-level interactions will also improve the fit of 50 percent or more of the models, and of those models, 50 percent or more will include a significant cross-level interaction fixed effect. In addition, the amount of Level 1 variance will decrease by $\sigma^2 = .02$ or greater and the amount of Level 2 variance will decrease by $\tau_{00} = .02$ or greater.

CHAPTER 6

MAIN STUDY: METHOD

Participants

Participants were recruited from the Arizona State University (ASU) psychology research participant pool and the Georgia Institute of Technology (Georgia Tech) psychology research participant pool. From the ASU sample, 239 participants completed Part 1 and 202 participants completed Part 2, and from the Georgia Tech sample, 270 participants completed Part 1 and 240 participants completed Part 2. The sample included both females and males (ASU: females = 58.4%, males = 41.6%; Georgia Tech: females = 50.6%, males = 49.4%). The average age of the participants in the ASU sample was 20.5 years (SD = 3.36), and in the Georgia Tech sample was 21.1 years (SD = 1.98). Participants were given one hour of study credit in exchange for participation.

Measures

Demographic and background questions. Each Georgia Tech participant was asked to provide his or her name, gender, race/ethnicity, and date of birth. The ASU Institutional Review Board indicated that the study should remain anonymous. As a result, each ASU participant was asked to provide his or her gender, race/ethnicity, and date of birth.

Personality questionnaire. The five 20-item scales from the IPIP written to assess the five factors of the NEO-PI-R (Costa Jr. & McCrae, 1992) were used to assess Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness (Goldberg et al., 2006). An extensive item development process was used to construct the IPIP scales (Buchanan, Johnson, & Goldberg, 2005; Goldberg et al., 2006). The sample consisted of thousands of participants who found the survey on the Internet through search engines (e.g., Yahoo, Lycos) and decided to complete a questionnaire with a personality inventory. The correlation between each IPIP item and the equivalent NEO-PI-R scale (e.g., NEO-PI-R Extraversion) was obtained and the IPIP items were rank ordered based on the effect sizes and combined into equivalent scales. An attempt was made to balance the number of positively and negatively worded items in each scale. The content of each item was reviewed to ensure that a theoretical rationale could be made for including the item in its scale and to remove any items that were redundant. Finally, reliability analyses were computed for each scale to ensure an appropriate level of internal consistency reliability. The internal consistency reliabilities for each of the 20-item IPIP scales varied from .85 to .91 (Buchanan et al., 2005; Goldberg et al., 2006). In the pilot study, the internal consistencies varied from .86 to .94 (see Table 4). The correlation between each IPIP scale and the equivalent NEO-PI-R scales varied from .88 to .93 ($\bar{r}$ = .90) after correcting for unreliability (Goldberg et al., 2006).

As a participant was excluded from the pilot study because of concerns of the responses the participant made, items from the Infrequency Scale were administered in an effort to identify participants who were not reading the questions in the study and providing invalid data (Chapman & Chapman, 1983). The Infrequency Scale has been used in a number of studies published in clinical psychology journals (e.g., Goodinga & Braun, 2004; Kerns, 2006; Pope & Kwapil, 2000; Raulin, 1984; Raulin & Wee, 1984) and was developed based on the infrequency scale used in the Personality Research Form. The entire Infrequency Scale comprises of 13 statements and is typically administered with a true/false response format. When the entire scale is used, two or three responses in the wrong direction usually indicate that a participants' responses may not be valid.

Feedback from several graduate students asked to review the questionnaires before administration to participants indicated that the items from the Infrequency Scale were distracting. An effort was made to select less districting items from the Infrequency Scale. In addition, the selected items from the Infrequency Scale were administered within other scales. Two of the items were imbedded in the BIS/BAS Scales, two of the items were imbedded in GRAPES, and one item was administered with the IPIP scales.

BIS/BAS functioning. Carver and White's (1994) BIS/BAS Scales and Ball and Zuckerman's (1990) Generalized Reward and Punishment Expectancy Scales (GRAPES) were used to assess BIS and BAS functioning. Carver and White (1994) developed and accumulated validity evidence for their 20-item BIS/BAS Scales across four studies. Several iterations of item writing and testing resulted in a BIS scale representing sensitivity to punishment and three BAS scales representing a tendency to pursue desired objectives (Drive), a desire for and a tendency to pursue potentially rewarding experiences (Fun), and a tendency to react positively in anticipation of a reward (Reward Responsiveness). Based on Cicchetti's (1994) guidelines, the internal consistency reliability estimates in the pilot study for BIS sensitivity (α = .74), BAS-Drive (α = .76), and BAS-Reward Responsiveness (α = .73) may be categorized as fair (α between .70 and .79), and for BAS-Fun (α = .66) may be categorized as unacceptable (α of .70 or below).

To examine the possibility of increasing the internal consistency reliabilities of the BIS/BAS Scales, the Spearman-Brown prophecy formula was computed for each scale (see Table 7). As the BIS/BAS Scales have few items per scale (four items to seven items) and based on the results of the Spearman-Brown formula, additional items were collected from similar measures and written to underlie each scale. Each scale was increased by about two to three times its original length.

Table 7. Predicted Reliability for the BIS/BAS Scales Based on the Spearman-Brown Prophecy Formula

	# of items	Reliability	N	New # of items	Predicted Reliability
BIS	7	0.73	1.5	10.5	0.80
BAS-Fun	4	0.73	1.5	6	0.80
BAS-RR	5	0.66	1.5	7.5	0.74
BAS-Drive	4	0.74	1.5	6	0.81
BIS	7	0.73	2	14	0.84
BAS-Fun	4	0.73	2	8	0.84
BAS-RR	5	0.66	2	10	0.80
BAS-Drive	4	0.74	2	8	0.85
BIS	7	0.73	2.5	17.5	0.87
BAS-Fun	4	0.73	2.5	10	0.87
BAS-RR	5	0.66	2.5	12.5	0.83
BAS-Drive	4	0.74	2.5	10	0.88
BIS	7	0.73	3	21	0.89
BAS-Fun	4	0.73	3	12	0.89
BAS-RR	5	0.66	3	15	0.85
BAS-Drive	4	0.74	3	12	0.90

Note. BAS–RR = BAS Reward Responsiveness.

Five items were added from the IPIP (Goldberg et al., 2006), three items from the Sensitivity to Punishment and Sensitivity to Reward Questionnaire (Torrubia et al., 2001), six items from the Attention to Positive and Negative Information Scale (Noguchi et al., 2006), five items from the UPPS Impulsive Behaviour Scale (Whiteside & Lynam, 2001), two items from the Penn State Worry Questionnaire (Meyer, Miller, Metzger, &

Borkovec, 1990), and one item from the Appetitive Motivation Scale (Jackson & Smillie, 2004). In some cases, the wording of the items was slightly modified. In addition, 24 items were written as described below. With the additional items, the BIS scale comprised of 21 items and the BAS scales comprised of 15 items each.

The BIS/BAS items and the additional items added from the other scales were examined to determine what areas of content could be tapped to provide a fuller representation of the construct underlying each of the four BIS/BAS Scales to write additional items. Writing highly similar or redundant items was avoided (see Clark & Watson, 1995). In general, the four scales did not tap individuals focusing their attention on either aversive stimuli (for the BIS scale) or appetitive stimuli (for the BAS scales). Additional items for the BIS scale were written to underlie a general and pervasive focus on threatening stimuli. BAS-Drive focuses rather narrowly on *going* after things. Additional items were written to provide a broader representation of appetitive motivation. BAS-Fun Seeking included two items on fun seeking and two items on excitement seeking, which seems to be consistent with the approach described by Carver and White (1994). As a result, the BAS-Fun scale correlates with both reward sensitivity and impulsivity (Smillie, Jackson et al., 2006). In an effort to construct a unidimensional scale, additional items were written to augment the fun-seeking items only by examining additional aspects of fun seeking and by including a greater variety of potentially fun activities. The number of BAS-Reward Responsiveness items was increased by writing items to incorporate additional types of rewards (e.g., awards, honors) and additional types of positive emotions (e.g., overjoyed, proud).

Ball and Zuckerman's (1990) GRAPES originated as an unpublished 120-item measure developed to assess individual's expectation of future life events based on past experiences. A factor analysis supported the two-factor structure of the measure. In the current version, each scale includes fifteen yes/no questions. Gomez et al. (2004) found fair internal consistency reliabilities for Reward Expectancy (α = .74) and Punishment Expectancy (α = .71). However, the internal consistency reliability estimates for Reward Expectancy (α = .63) and Punishment Expectancy (α = .60) were lower in the pilot study (see also Zelenski & Larsen, 1999). In an effort to increase the internal consistency of the scales, each item was administered using a 6-point scale (1 = strongly disagree, 6 = strongly agree) to increase the amount of variance that each item contributed to the overall scale score instead of the yes/no format originally used by Ball and Zuckerman (1990).

Course Rating Tasks. Two course rating tasks were used. For the first task, participants were asked to recall the best and worst elective courses they had taken in the last two years. Participants were instructed to consider both college and high school classes to ensure that lower-level students could come up with a best and worst class. For both the best and worst elective courses recalled, participants were asked to indicate the department (or general subject area) in which the course was offered (e.g., psychology), to rate the course on eight items, and to list three distinctive features of the course.

In the second task, participants were presented with a series of hypothetical course descriptions, and instructed to consider each course as an elective course. Each course description included a course title, a brief description of the course, and three statements made by other students. The participants were told that the statements were made by students who had taken the course. To further ensure that the participants considered the source of information reputable, participants were also told that the statements provided were those made by college students with a grade point average of 3.0 or higher. The content and layout of each course description was designed to resemble the layout used by course evaluation websites commonly used by students to select courses. After reviewing each course description, participants were asked to rate the course using a rating scale with eight items.

Each statement commented on two features of the course, so that the information participants obtained from reading the three statements covered six features of the course in six comments. Findings obtained in the pilot study were used to construct and systematically vary each student comment in terms of the number of aversive, appetitive, and neutral features. Comments associated with BIS sensitivity were constructed using the aversive end of the course feature items, comments associated with BAS sensitivity were constructed using the appetitive end of the course feature items, and neutral comments that were not associated with BIS or BAS sensitivity were constructed based on a description of the course feature that would fall between the aversive and appetitive ends of the course feature items. An attempt was made to select course feature items that correlated with only the negatively-toned characteristics for the aversive comments and to select course features items that correlated with only the positively-toned characteristics for the appetitive comments. As a result, the emotional valence of each comment may be characterized as either appetitive, aversive, or neutral.

As shown in the design scheme presented in Table 6, each pattern of comment valences was used three separate times under three different courses and with different comments. For example, each study participant rated course descriptions that contained six rewarding comments, zero neutral comments, and zero aversive comments three times with three different course titles and with three different sets of comments. Six forms of the course rating task were assembled to reduce order effects associated with a particular order.

Based on the results obtained in the pilot study, course contents (e.g., Psychology of Personality) of a similar level of interest that did not load highly onto the same factor were used within each comment valence group. Each course content was used two to four times (as Section A, B, C, and D) yielding 36 separate course ratings (see Table 6). In addition, as suggested by past researchers (Aiman-Smith, Scullen, & Barr, 2002), four warm-up course descriptions were presented and four course descriptions were presented twice to estimate the reliability of the task resulting in a total of 44 course description ratings. As suggested by Aiman-Smith et al. (2002), the four warm-up course descriptions were not scored. Before analyzing the ratings, the ratings from the course descriptions presented twice to estimate reliability were averaged.

Procedure

Participants were recruited using online recruitment systems (i.e., Experimetrix, SONA Systems). After signing up for the study, participants were allowed to access a link through the online recruitment system that directed them to the first part of the study. Before starting the first part of the study, participants were presented with a consent form and asked to continue only if they wished to participate in the study. The first part of the study contained the demographic and individual differences measures. After completing the first part of the study, participants were sent a link over electronic mail to access the second part of the study. At a minimum, participants were contacted the following day, and at a maximum, within 72 hours. The second part of the study included the best/worst course rating task followed by the course description rating task.

CHAPTER 7

MAIN STUDY: RESULTS

To be included in the dataset for analysis, participants had to complete at least the first measure of the Part 1 questionnaire. Participants were removed from the dataset based on the results of questions from the Infrequency Scale (Chapman & Chapman, 1983), a short scale created for this study similar to the Variable Response Inconsistency (VRIN) scale used on the Minnesota Multiphasic Personality Inventories and the Multidimensional Personality Questionnaire as described by Tellegen (1988; see also Berry et al., 1992; Berry et al., 1991; Bruehl, Lofland, Sherman, & Carlson, 1998; Wetter, Baer, Berry, Smith, & Larsen, 1992), an examination of the time taken to complete each part, and an examination of outliers. All of this information was pooled and considered on a case-by-case basis.

Analyses are presented for both the Arizona State University (ASU) sample and the Georgia Tech sample separately and pooled together as one sample. Interpretation of the results focuses on the ASU sample and the Georgia Tech sample as the results from the combined sample are redundant after a review of the two individual samples. In addition, although the hypotheses focused on just the person characteristics derived from the Reward Sensitivity Theory, data analysis also included Neuroticism and Extraversion. As a result, the predictors are usually referred to collectively as the negatively- and positively-toned characteristics. First, the descriptive statistics of the predictors are reviewed. Next, the intercorrelation among the predictors is reviewed, which allows for an investigation of the first two hypotheses. The descriptive statistics of the course ratings are examined next. Polynomial contrasts were computed to examine the predictions made in the third hypothesis. It was predicted in Hypothesis 3 that participants would rate course descriptions with more positive comments more highly and course descriptions with more negative comments more negatively. Consistent with the Reward Sensitivity Theory and related research, only the following pairs of predictor scales were examined for the remaining analyses: the BIS/BAS Scales (the BIS scale and a BAS scale with all BAS items combined), the revised BIS/BAS Scales (the revised BIS scale and the revised BAS scale with all revised BAS items combined), Punishment Expectancy and Reward Expectancy from GRAPES, and Neuroticism and Extraversion from the IPIP scales. Correlations and regression results are examined next to determine the relationships between the predictors and criteria (Hypotheses 4 and 5). Finally, to evaluate the predictions made in Hypothesis 6, the results from multilevel modeling analyses are examined to determine whether the negatively- and positively-toned characteristics predict course ratings in models that also include the condition of the course description rating task (i.e., the pattern of comment valences from the course descriptions).

Predictors

Before examining the hypotheses, the psychometric properties of the measures were examined to determine whether any changes to the items included in the scales were warranted. Results from the ASU sample and the Georgia Tech sample were compared when making item revision decisions. Table 8 displays the means, standard deviations, and internal consistency reliability estimates of the predictor scales. Guidelines suggested by Cicchetti (1994) were used to categorize the internal consistency reliability

Table 8. Predictor Descriptive Statistics

	# of items	ASU			Georgia Tech			Both		
		M	SD	α	M	SD	α	M	SD	α
BIS	7	4.2	.78	.77	4.4	.80	.82	4.3	.80	.80
BAS	13	4.6	.52	.81	4.5	.47	.75	4.6	.49	.78
BAS-Fun	4	4.5	.74	.64	4.3	.72	.62	4.4	.73	.63
BAS-RR	5	5.0	.56	.74	5.0	.50	.65	5.0	.53	.70
BAS-Drive	4	4.2	.77	.78	4.1	.77	.78	4.2	.77	.78
BIS+	21	3.8	.61	.89	3.9	.67	.93	3.9	.65	.92
BAS+	43	4.4	.38	.90	4.3	.35	.87	4.4	.37	.89
BAS-Fun+	14	4.4	.55	.83	4.2	.50	.78	4.3	.53	.81
BAS-RR+	14	4.6	.47	.86	4.6	.44	.83	4.6	.45	.85
BAS-Drive+	15	4.5	.45	.81	4.5	.45	.82	4.5	.45	.81
Punishment Expectancy	15	3.6	.56	.70	3.6	.54	.69	3.6	.55	.69
Reward Expectancy	11	4.1	.64	.76	4.0	.65	.80	4.0	.65	.78
Neuroticism	20	2.7	.61	.89	2.7	.77	.94	2.7	.70	.92
Extraversion	20	3.6	.72	.93	3.4	.74	.94	3.5	.74	.94
Agreeableness	20	3.5	.49	.84	3.6	.49	.85	3.5	.49	.84
Conscientiousness	20	3.6	.56	.90	3.6	.63	.92	3.6	.60	.91
Openness	20	3.5	.54	.85	3.6	.56	.86	3.5	.55	.85

Note. BAS-RR = BAS Reward Responsiveness.

estimates obtained in the main study. Cicchetti indicated that an internal consistency below .70 is unacceptable, between .70 and .79 is fair, between .80 and .89 is good, and above .90 is excellent.

No changes were made to the BIS/BAS Scales. Across all of the BIS/BAS Scales, the internal consistencies varied from the unacceptable range to the good range for BIS (α_{ASU} = .77, $\alpha_{Georgia\ Tech}$ = .82), BAS (α_{ASU} = .81, $\alpha_{Georgia\ Tech}$ = .75), BAS-Fun (α_{ASU} = .64, $\alpha_{Georgia\ Tech}$ = .62), BAS-Reward Responsiveness (α_{ASU} = .74, $\alpha_{Georgia\ Tech}$ = .65), and BAS-Drive (α_{ASU} = .78, $\alpha_{Georgia\ Tech}$ = .78).

Additional items were selected from existing measures and written to underlie each scale of the BIS/BAS Scales in an attempt to increase the internal consistency reliability estimates. A plus was added to the end of each scale name (e.g., BIS+) to distinguish the revised scale from the original BIS/BAS Scales. Of the additional items considered, one items was removed from the BIS+, BAS-Fun+, and BAS-Reward Responsiveness+ scales for a slight increase in the reliability estimate. Otherwise, all of the additional items were included. The internal consistency reliability estimates were good to excellent for BIS+ (α_{ASU} = .89, $\alpha_{Georgia\ Tech}$ = .93) and BAS+ (α_{ASU} = .90, $\alpha_{Georgia\ Tech}$ = .87), and for BAS-Fun+, BAS-Reward Responsiveness+, and BAS-Drive+ varied from .79 to .87.

GRAPES was administered with a 6-point scale instead of the yes/no format used by the scale creators (Ball and Zuckerman, 1990). Four items were removed from Reward Expectancy in an effort to increase the reliability estimate; no items were removed from the Punishment Expectancy scale. Removing items from the Punishment Expectancy scale did not lead to an increase in internal consistency. The internal consistency reliability estimate increased for Reward Expectancy after removing four items (pilot study: α = .65, main study: α_{ASU} = .76, $\alpha_{Georgia\ Tech}$ = .80), but only a slight improvement was found with Punishment Expectancy (pilot study: α = .68, main study: α_{ASU} = .70, $\alpha_{Georgia\ Tech}$ = .69).

The internal consistencies for the IPIP scales were similar to the results observed in the pilot study. The reliability estimates for Neuroticism, Extraversion, Agreeableness, Conscientiousness, and Openness across the samples varied from .84 to .94 (pilot study: α varied from .86 to .94).

As discussed in the Results/Discussion section for the pilot study, $\alpha < .70$ will not be used as cut off for excluding variables in later analyses. The internal consistency reliability of a scale confounds reliability and the heterogeneity of the items included in the scale, and is a function of the number of items included in the scale (Ackerman &

Humphreys, 1991). In contrast to the Pilot Study, only Punishment Expectancy from GRAPES (and not Reward Expectancy) had an unacceptable internal consistency reliability estimate. As Punishment Expectancy assesses a broadly defined construct (i.e., BIS sensitivity), a lower internal consistency reliability estimate may not be indicative of low reliability. Similar to the Pilot study, the internal consistency of several BAS scales fell into the unacceptable range—most likely due to the small number of items included in each BAS scale. BAS-Fun and BAS-Reward Responsiveness were included in the analysis of the first, second, and fourth hypotheses so that the results could be compared with the corresponding scales from the revised BIS/BAS Scales.

Hypotheses 1 and 2: Convergent Validity

Table 9 through Table 11 present the intercorrelation among the predictor scales. The convergent validity of the scales designed to assess the person characteristics derived from Reward Sensitivity Theory was examined to determine whether the predictions made in Hypothesis 1 were supported. It was predicted in Hypothesis 1a that the BIS scale would be highly correlated (r between .40 and .60) with Punishment Expectancy. This hypothesis was supported across both samples for both the BIS and BIS+ scales (r varied between .42 and .61), except that BIS+ and Punishment Expectancy were correlated more highly than expected in the Georgia Tech sample ($r = .61$). It was predicted in Hypothesis 1b that the BAS scales would be highly correlated (r between .40 and .60) with Reward Expectancy. A number of the effect sizes were of a medium size rather than a large size and, thus, below the predicted range (see Cohen, 1988). For the ASU sample, Hypothesis 1b was supported for BAS+ ($r = .48$) and BAS-Drive+ ($r = .41$), but not supported for BAS ($r = .39$), BAS-Fun ($r = .27$), BAS-Reward

Table 9. ASU Predictor Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. BIS	1.00																
2. BAS	0.07	1.00															
3. BAS-Fun	-0.14*	0.76*	1.00														
4. BAS-RR	0.41*	0.72*	0.31*	1.00													
5. BAS-Drive	-0.09	0.80*	0.42*	0.38*	1.00												
6. BIS+	0.88*	0.06	-0.14*	0.34*	-0.06	1.00											
7. BAS+	0.18*	0.79*	0.60*	0.68*	0.53*	0.09	1.00										
8. BAS-Fun+	-0.09	0.67*	0.83*	0.31*	0.38*	-0.12	0.76*	1.00									
9. BAS-RR+	0.34*	0.62*	0.28*	0.80*	0.36*	0.25*	0.83*	0.41*	1.00								
10. BAS-Drive+	0.18*	0.62*	0.28*	0.55*	0.58*	0.08	0.77*	0.33*	0.59*	1.00							
11. PE	0.42*	0.05	-0.05	0.18*	-0.01	0.51*	0.16*	0.05	0.19*	0.12	1.00						
12. RE	-0.17*	0.39*	0.27*	0.24*	0.36*	-0.26*	0.48*	0.37*	0.39*	0.41*	-0.13*	1.00					
13. Neuroticism	0.56*	-0.05	-0.14*	0.15*	-0.11	0.74*	-0.12	-0.20*	0.03	-0.12	0.47*	-0.35*	1.00				
14. Extraversion	-0.22*	0.39*	0.41*	0.15*	0.32*	-0.32*	0.51*	0.58*	0.34*	0.25*	-0.14*	0.60*	-0.40*	1.00			
15. Agreeableness	0.12	-0.04	0.00	0.09*	-0.16*	-0.10	0.12	0.08	0.13*	0.05	-0.17*	0.02	-0.34*	0.22*	1.00		
16. Conscientiousness	0.07	0.17*	-0.02	0.22*	0.19*	-0.07	0.38*	0.05	0.32*	0.61*	0.07	0.35*	-0.21*	0.23*	0.20*	1.00	
17. Openness	-0.02	0.18*	0.27*	0.18*	-0.02	-0.11	0.27*	0.29*	0.18*	0.15*	-0.01	0.10	-0.04	0.26*	0.14*	0.02	1.00

Note. BAS-RR = BAS Reward Responsiveness, PE = Punishment Expectancy, RE = Reward Expectancy.
*$p < .05$.

Table 10. Georgia Tech Predictor Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. BIS	1.00																
2. BAS	.01	1.00															
3. BAS-Fun	-.26*	.69*	1.00*														
4. BAS-RR	.35*	.66*	.14*	1.00													
5. BAS-Drive	-.01	.80*	.31*	.35*	1.00												
6. BIS+	.91*	.02	-.27*	.33*	.03	1.00											
7. BAS+	.03	.81*	.59*	.58*	.59*	-.02	1.00										
8. BAS-Fun+	-.23*	.61*	.84*	.17*	.28*	-.29*	.73*	1.00									
9. BAS-RR+	.32*	.58*	.20*	.77*	.33*	.28*	.75*	.30*	1.00								
10. BAS-Drive+	-.04	.62*	.22*	.37*	.72*	-.06	.73*	.28*	.38*	1.00							
11. PE	.54*	.04	-.19*	.25*	.06	.61*	.00	-.20*	.17*	.00	1.00						
12. RE	-.31*	.36*	.22*	.16*	.37*	-.41*	.51*	.37*	.26*	.56*	-.25*	1.00					
13. Neuroticism	.65*	-.03	-.25*	.18*	.02	.83*	-.12*	-.30*	.13*	-.14*	.54*	-.46*	1.00				
14. Extraversion	-.21*	.33*	.40*	.04	.24*	-.33*	.44*	.57*	.16*	.25*	-.23*	.50*	-.36*	1.00			
15. Agreeableness	-.02	.01	.03	.09	-.08	-.14*	.16*	.13*	.09	.11	-.19*	.11	-.32*	.20*	1.00		
16. Conscientiousness	-.11	.12	-.14*	.07	.32*	-.16*	.25*	-.08	.08	.63*	-.07	.49*	-.27*	.20*	.28*	1.00	
17. Openness	-.03	.06	.20*	-.02	-.06	-.09	.17*	.26*	.07	.05	.00	.19*	-.10	.26*	.23*	.01	1.00

Note. BAS-RR = BAS Reward Responsiveness, PE = Punishment Expectancy, RE = Reward Expectancy.
*p < .05.

Table 11. Both Universities Predictor Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. BIS	1.00																
2. BAS	0.03	1.00															
3. BAS-Fun	-0.22*	0.73*	1.00														
4. BAS-RR	0.37*	0.69*	0.23*	1.00													
5. BAS-Drive	-0.05	0.80*	0.37*	0.37*	1.00												
6. BIS+	0.89*	0.03	-0.22*	0.33*	-0.01	1.00											
7. BAS+	0.10*	0.80*	0.60*	0.64*	0.56*	0.02	1.00										
8. BAS-Fun+	-0.17*	0.65*	0.84*	0.25*	0.34*	-0.22*	0.75*	1.00									
9. BAS-RR+	0.32*	0.60*	0.24*	0.78*	0.34*	0.26*	0.79*	0.36*	1.00								
10. BAS-Drive+	0.05	0.62*	0.26*	0.46*	0.66*	0.00	0.75*	0.31*	0.48*	1.00							
11. PE	0.48*	0.05	-0.12*	0.22*	0.03	0.56*	0.08	-0.07	0.18*	0.06	1.00						
12. RE	-0.25*	0.37*	0.25*	0.20*	0.37*	-0.35*	0.50*	0.37*	0.32*	0.49*	-0.20*	1.00					
13. Neuroticism	0.60*	-0.04	-0.20*	0.17*	-0.03	0.79*	-0.12*	-0.25*	0.08	-0.13*	0.50*	-0.41*	1.00				
14. Extraversion	-0.22*	0.37*	0.42*	0.10*	0.28*	-0.33*	0.48*	0.58*	0.25*	0.26*	-0.18*	0.55*	-0.37*	1.00			
15. Agreeableness	0.05	-0.02	0.01	0.09*	-0.12*	-0.12*	0.14*	0.10*	0.11*	0.08	-0.18*	0.07	-0.33*	0.20*	1.00		
16. Conscientiousness	-0.03	0.14*	-0.08	0.14*	0.26*	-0.12*	0.31*	-0.02	0.19*	0.62*	-0.01	0.43*	-0.25*	0.21*	0.24*	1.00	
17. Openness	-0.02	0.11*	0.22*	0.07	-0.05	-0.09*	0.21*	0.26*	0.12*	0.09*	-0.01	0.15*	-0.08	0.25*	0.19*	0.02	1.00

Note. BAS-RR = BAS Reward Responsiveness, PE = Punishment Expectancy, RE = Reward Expectancy.
*$p < .05$.

Responsiveness (r = .24), BAS-Drive (r = .36), BAS-Fun+ (r = .37), or BAS-Reward Responsiveness+ (r = .36). For the Georgia Tech sample, Hypothesis 1b was supported for BAS+ (r = .51) and BAS-Drive+ (r = .56), but not supported for BAS (r = .36), BAS-Fun (r = .22), BAS-Reward Responsiveness (r = .16), BAS-Drive (r = .37), BAS-Fun+ (r = .37), or BAS-Reward Responsiveness+ (r = .26).

The convergent validity of the scales designed to assess the behavioral inhibition system supported predictions made in Hypothesis 1a in all but one comparison when the effect size was higher than predicted. The convergent validity of the scales designed to assess the behavioral activation system supported predictions made in Hypothesis 1b in less than half of the comparisons with the original BAS scales and half of the comparisons with the revised BAS scales. In all cases, lack of support resulted from finding a significant, positive correlation that did not fall within the predicted range (r between .40 and .60). Moreover, when examining whether the confidence intervals of the correlations fall into the predicted range and determining whether the correlations fell into the predicted range after correcting for attenuation due to unreliability in the measures, only BAS-Fun and BAS-Reward Responsiveness from both samples and BAS-Reward Responsiveness+ from the Georgia Tech sample did not meet expectations.

The convergent validity between the scales designed to assess the person characteristics derived from the Reward Sensitivity Theory and the corresponding scales from the IPIP representing the Big Five was examined to determine whether the predictions made in Hypothesis 2 were supported. It was predicted in Hypothesis 2a that the BIS scale and Punishment Expectancy would be correlated (r between .40 and .60) with Neuroticism. For the ASU sample, the results supported the predictions made in

Hypothesis 2a for BIS (*r* = .56) and Punishment Expectancy (*r* = .47), but not for BIS+ (*r* = .74). For the Georgia Tech sample, the results supported predictions made in Hypothesis 2a for just Punishment Expectancy (*r* = .54), but not for BIS (*r* = .65) or BIS+ (*r* = .83). In all cases, when a correlation did not meet expectations stated in Hypothesis 2a, the effect size of the correlation was higher than the predicted range.

It was predicted in Hypothesis 2b that the BAS scales and Reward Expectancy would be correlated (*r* between .40 and .60) with Extraversion. With the ASU sample, the results supported the predictions made in Hypothesis 2b for BAS-Fun (*r* = .41), BAS+ (*r* = .51), BAS-Fun+ (*r* = .58), and Reward Expectancy (*r* = .60), but not for BAS (*r* = .39), BAS-Reward Responsiveness (*r* = .15), BAS-Drive (*r* = .32), BAS-Reward Responsiveness+ (*r* = .34), or BAS-Drive+ (*r* = .25). With the Georgia Tech sample, the results supported the predictions made in Hypothesis 2b for BAS-Fun (*r* = .40), BAS+ (*r* = .44), BAS-Fun+ (*r* = .57), and Reward Expectancy (*r* = .50), but not for BAS (*r* = .33), BAS-Reward Responsiveness (*r* = .04), BAS-Drive (*r* = .24), BAS-Reward Responsiveness+ (*r* = .16), or BAS-Drive+ (*r* = .25). The correlation between BAS-Reward Responsiveness was not significant, otherwise, the correlations that did not meet the expectations stated in Hypothesis 2b were positive and significant, but below the expected range of effect sizes. In addition, when examining the confidence intervals, only BAS-Reward Responsiveness and BAS-Drive+ from both samples and BAS-Drive and BAS-Reward Responsiveness+ from the Georgia Tech sample have ranges that did not fall within the predicted range. The same pattern of results was obtained after correcting the correlations for attention due to unreliability in the measures, except that the corrected correlations for BAS-Drive from the ASU sample and BAS from the

Georgia Tech sample did not fall within the predicted range.

The predictions in Hypotheses 1 and 2 were made to assess the convergent validity of the measures designed to assess the behavioral inhibition system and the behavioral activation system. Other than the nonsignificant correlation with BAS-Reward Responsiveness from the BIS/BAS Scales, the results do not present any areas for concern that would adversely affect the interpretation of later analyses. The results for the measures designed to assess the behavioral inhibition system either met or exceeded expectations. On the other hand, the results from the measures designed to assess the behavioral activation system either met or fell below expectations. However, when correlations fell below expectations the effect size was significant in all cases except with BAS-Reward Responsiveness, which is consistent with past findings (e.g., Torrubia et al., 2001).

Criteria

An initial reliability analysis of the ratings from the course description rating task indicated that removing the three negatively worded rating items[2] improved the internal consistency of the rating scale. Based on the issues associated with using items that are not continuous (Bernstein, 1988, Nunnaly & Bernstein, 1994), a factor analysis was not performed. However, as the separation of criteria into positively-toned and negatively-toned scales is consistent with Reward Sensitivity Theory and past research, the ratings items were divided into a negatively-worded scale and a positively-worded scale. All of the negatively worded items were reverse scored with lower ratings

[2] Each rating item from the course description rating task is an average of three to four items with the same wording from different course descriptions that have the same pattern of comment valences and different course content. I assumed that the term rating item composite, although more appropriate, would lead to more confusion.

reflecting more negative ratings and higher ratings reflecting more positive ratings.

Best/worst course rating task. Before rating the course descriptions, participants were asked to list the department (e.g., psychology) or general area (e.g., math) of the best and worst courses they had taken in the last two years—high school or college—and to rate the courses using a similar rating scale as the course description rating task. Only departments/general areas listed by five or more participants are reported (see Table 12). As both samples were taken from psychology subject pools, the frequency of the selection of psychology as a best course was not unexpected. There is some similarity between the responses from the ASU sample and the Georgia Tech sample (e.g., Psychology and Foreign Language listed frequently as best course).

Several departments/general areas appear on the best list and the worst list (e.g., Art/Fine Art, Psychology), which could lead to several conclusions. For example, level

Table 12. List of Best/Worst Courses

ASU				Georgia Tech			
Pos.		Neg.		Pos.		Neg.	
Course Dept./Area	%	Course Dept./Area	%	Course Dept./Area	%	Course Dept./Area	%
Psychology	18.3%	Art/Fine Art	11.2%	Psychology	20.9%	Economics	8.5%
Art/Fine Art	15.2%	Math	7.1%	Foreign Language	7.9%	Math	8.1%
Foreign Language	6.1%	English	5.1%	Computer Science	6.7%	Computer Science	7.2%
Business	5.6%	Science	5.1%	Math	5.4%	Engineering	6.0%
Music	4.6%	Performance Arts	5.1%	Art/Fine Art	4.6%	History	6.0%
English	3.6%	Psychology	4.6%	Science	4.6%	Psychology	6.0%
Sociology	3.6%	Foreign Language	4.1%	Business	3.8%	Health	5.5%
Math	3.0%	History	4.1%	Economics	3.3%	English	4.7%
Science	2.5%	Sociology	4.1%	Engineering	3.3%	Business	3.8%
Performance Arts	2.5%	Philosophy	3.0%	History	3.3%	Foreign Language	3.4%
		Physical Education	3.0%	Music	3.3%	Physics	3.4%
		Business	2.5%	English	2.5%	International Affairs	3.0%
		Chemistry	2.5%	Chemistry	2.1%	Art/Fine Art	2.6%
		Computer Science	2.5%	Physical Education	2.1%	Biology	2.1%
		Economics	2.5%			Music	2.1%
						Political Science	2.1%

of interest may vary by participant or a course from a particular department or general area may be liked or disliked for a variety of reasons. Table 13 displays the mean and standard deviation for the ratings from the best and worst course rating task. Comparisons with the results from the course description rating task should be limited as participants may select a course as the best or worst for reasons other than the department or general area of the course and participants were limited to selecting courses they had taken in the last two years.

Table 13. Best/Worst Course Rating Descriptives

		ASU		Georgia Tech		Both	
Rating	Tone	M	SD	M	SD	M	SD
Best Course Rating	Pos.	5.32	.76	5.37	.64	5.35	.70
Best Course Rating	Neg.	3.43	1.18	3.35	1.14	3.39	1.16
Worst Course Rating	Pos.	3.28	.91	3.07	.91	3.16	.92
Worst Course Rating	Neg.	3.33	1.53	3.23	1.54	3.27	1.53

Course description rating task. The next set of analyses examined the reliability of the ratings from the course description rating task. Massad (1977) indicated that while a test-retest reliability between .60 and .84 was acceptable, a value of .85 or higher was recommended. As with the predictor internal consistency reliability estimates, the guidelines reported by Cicchetti (1994) are used to categorize the internal consistency reliability estimates obtained in the main study for the criteria.

Four course descriptions were administered twice to obtain a test-retest reliability estimate. The test-retest reliability estimates from the combined sample for Psychology of Personality (r_{pos} = .68, r_{neg} = .49), Introduction to Photography (r_{pos} = .62, r_{neg} = .45), Exploring the Universe (r_{pos} = .72, r_{neg} = .46), and Introduction to Anthropology (r_{pos} = .69, r_{neg} = .51) were all below the .85 value recommended by Massad (1977).

Table 14 displays the mean, standard deviation, and internal consistency reliability estimate for each rating by course description. The internal consistency reliabilities vary from .81 to .94 with an average consistency of .89 for the ASU sample and .88 for the Georgia Tech sample. For the ASU sample and based on guidelines suggested by Cicchetti (1994), 27 of the of the consistencies fell into the excellent range and 13 in the good range for the positively-toned ratings, and six of the consistencies fell into the excellent range and 34 into the good range for the negatively-toned ratings. For the Georgia Tech sample and based on guidelines suggested by Cicchetti, 22 of the of the consistencies fell into the excellent range and 18 in the good range for the positively-toned ratings, and four of the consistencies fell into the excellent range and 36 into the good range for the negatively-toned ratings.

Table 15 displays the means, standard deviations, and internal consistency reliability estimates of the ratings by condition of the course description rating task. Table 15 provides the most appropriate reliability estimates as the remaining analyses were examined by task condition. None of the reliability estimates were below .88 and most were .90 or higher (83.3 percent for the ASU sample and 67.7 percent for the Georgia Tech sample). The average internal consistency for the ASU sample was .91 and the average internal consistency for the Georgia Tech sample was .90. Based on Cicchetti's (1994) guidelines, all of the reliability estimates in Table 15 fall into, at least, the good range with the majority falling in the excellent range.

Hypothesis 3: Manipulation check

It was predicted in the third hypothesis that participants would rate course descriptions with fewer aversive comments and more positive comments more highly

Table 14. Criteria Descriptive Statistics by Course Description

					ASU			Georgia Tech			Both		
Content	Valence	# of RCs	# of NCs	# of ACs	M	SD	α	M	SD	α	M	SD	α
Psychology of Personality (1)	Pos.	6	0	0	4.71	.79	.89	4.65	.81	.91	4.68	.80	.90
Psychology of Personality (1)	Neg.	6	0	0	3.31	.99	.91	3.80	.91	.86	3.59	.97	.89
Psychology of Personality (2)	Pos.	6	0	0	4.42	.88	.92	4.38	.82	.88	4.40	.84	.90
Psychology of Personality (2)	Neg.	6	0	0	3.50	.97	.88	3.78	.91	.89	3.65	.95	.89
Entrepreneurship	Pos.	6	0	0	4.31	1.14	.94	4.36	.92	.89	4.34	1.03	.92
Entrepreneurship	Neg.	6	0	0	3.36	1.02	.90	3.70	.93	.88	3.54	.99	.89
Intro. to Photography	Pos.	6	0	0	4.35	1.01	.92	4.37	1.05	.92	4.36	1.03	.92
Intro. to Photography	Neg.	6	0	0	3.82	.98	.88	4.10	.88	.86	3.98	.94	.87
Entrepreneurship	Pos.	0	6	0	4.25	1.07	.90	4.38	.94	.88	4.31	1.00	.89
Entrepreneurship	Neg.	0	6	0	3.52	1.00	.90	3.93	.86	.84	3.75	.95	.88
Intro. to Photography	Pos.	0	6	0	4.13	1.03	.91	4.09	1.00	.90	4.11	1.01	.91
Intro. to Photography	Neg.	0	6	0	3.88	1.04	.91	3.91	.96	.87	3.85	.99	.89
Psychology of Personality	Pos.	0	6	0	4.17	.91	.91	4.11	.86	.89	4.14	.88	.90
Psychology of Personality	Neg.	0	6	0	3.09	.88	.88	3.38	.86	.89	3.25	.88	.89
Intro. to Photography (1)	Pos.	0	0	6	3.63	1.17	.92	3.43	1.06	.89	3.52	1.12	.90
Intro. to Photography (1)	Neg.	0	0	6	2.68	.96	.86	2.63	1.00	.88	2.64	.99	.87
Intro. to Photography (2)	Pos.	0	0	6	3.47	1.00	.89	3.28	1.02	.89	3.36	1.01	.89
Intro. to Photography (2)	Neg.	0	0	6	2.86	.91	.86	2.86	1.02	.91	2.86	.97	.89
Psychology of Personality	Pos.	0	0	6	3.85	1.01	.92	3.68	.98	.90	3.76	.99	.91
Psychology of Personality	Neg.	0	0	6	2.60	.80	.84	2.71	.95	.89	2.66	.89	.87
Entrepreneurship	Pos.	0	0	6	3.46	1.09	.92	3.42	.99	.90	3.44	1.03	.91
Entrepreneurship	Neg.	0	0	6	2.65	.87	.88	2.74	.93	.88	2.70	.90	.88
Criminology	Pos.	3	3	0	4.24	.88	.89	4.15	.93	.89	4.19	.91	.89
Criminology	Neg.	3	3	0	2.88	.79	.81	2.99	.85	.85	2.94	.83	.84
Exploring the Universe	Pos.	3	3	0	4.13	.98	.92	4.27	.96	.91	4.21	.97	.91
Exploring the Universe	Neg.	3	3	0	3.46	.95	.88	3.74	.89	.85	3.62	.92	.87
Intro. to Film	Pos.	3	3	0	4.16	.91	.90	4.03	.97	.90	4.09	.94	.90
Intro. to Film	Neg.	3	3	0	3.46	.90	.86	3.61	1.01	.91	3.54	.96	.89
Exploring the Universe (1)	Pos.	0	3	3	3.81	.99	.89	3.84	1.06	.92	3.82	1.03	.90
Exploring the Universe (1)	Neg.	0	3	3	2.88	.95	.87	2.93	.90	.81	2.90	.92	.84
Exploring the Universe (2)	Pos.	0	3	3	3.64	.91	.88	3.69	.97	.90	3.67	.94	.89
Exploring the Universe (2)	Neg.	0	3	3	3.01	.88	.88	3.10	.88	.88	3.06	.88	.88

Table 14 (continued).

Content	Valence	# of RCs	# of NCs	# of ACs	ASU M	ASU SD	ASU α	Georgia Tech M	Georgia Tech SD	Georgia Tech α	Both M	Both SD	Both α
Intro. to Film	Pos.	0	3	3	4.00	.93	.90	3.96	.83	.86	3.98	.87	.88
Intro. to Film	Neg.	0	3	3	3.23	.91	.86	3.37	.95	.89	3.31	.93	.87
Criminology	Pos.	0	3	3	4.04	.84	.89	3.98	.87	.90	4.01	.86	.89
Criminology	Neg.	0	3	3	3.21	.86	.86	3.37	.88	.90	3.30	.88	.88
Intro. to Film	Pos.	3	0	3	4.11	.95	.89	3.97	.87	.86	4.03	.91	.87
Intro. to Film	Neg.	3	0	3	3.18	.95	.88	3.19	.96	.87	3.18	.96	.87
Criminology	Pos.	3	0	3	4.28	.85	.89	4.13	.82	.87	4.20	.84	.88
Criminology	Neg.	3	0	3	3.07	.87	.88	3.31	.83	.85	3.20	.87	.87
Exploring the Universe	Pos.	3	0	3	3.58	.96	.89	3.72	.99	.91	3.66	.97	.90
Exploring the Universe	Neg.	3	0	3	2.78	.91	.89	2.85	.88	.87	2.82	.89	.88
Intro. to Abnormal Psychology	Pos.	4	2	0	4.67	.92	.92	4.72	.84	.89	4.70	.87	.91
Intro. to Abnormal Psychology	Neg.	4	2	0	3.54	1.00	.89	3.94	.94	.86	3.76	.99	.88
Intro. to Philosophy	Pos.	4	2	0	4.10	1.02	.93	4.18	.96	.91	4.15	.98	.92
Intro. to Philosophy	Neg.	4	2	0	3.24	.88	.87	3.57	.87	.86	3.42	.89	.87
Religions of the World	Pos.	4	2	0	4.30	1.10	.92	4.31	1.04	.91	4.31	1.78	.91
Religions of the World	Neg.	4	2	0	3.68	1.10	.90	3.98	1.00	.89	3.84	1.05	.90
Intro. to Philosophy	Pos.	2	4	0	3.67	1.10	.92	3.75	1.05	.90	3.72	1.78	.91
Intro. to Philosophy	Neg.	2	4	0	2.72	.90	.86	2.84	.90	.87	2.79	.90	.87
Religions of the World	Pos.	2	4	0	4.01	1.07	.90	4.05	1.03	.87	4.03	1.56	.89
Religions of the World	Neg.	2	4	0	3.65	.97	.88	3.89	.95	.86	3.78	.97	.87
Intro. to Abnormal Psychology	Pos.	2	4	0	4.40	.82	.90	4.36	.87	.90	4.38	.85	.90
Intro. to Abnormal Psychology	Neg.	2	4	0	3.43	.91	.89	3.80	.86	.88	3.63	.90	.89
Religions of the World	Pos.	0	4	2	3.84	1.12	.90	3.83	1.07	.90	3.84	1.10	.90
Religions of the World	Neg.	0	4	2	2.83	.88	.84	3.01	.93	.85	2.93	.91	.85
Intro. to Abnormal Psychology	Pos.	0	4	2	4.19	.92	.91	4.23	.89	.88	4.21	.90	.89
Intro. to Abnormal Psychology	Neg.	0	4	2	3.26	.94	.90	3.65	.94	.88	3.47	.96	.89
Intro. to Philosophy	Pos.	0	4	2	3.62	.92	.89	3.72	.89	.88	3.67	.90	.88
Intro. to Philosophy	Neg.	0	4	2	3.01	.77	.83	3.38	.87	.89	3.21	.85	.87

Table 14 (continued).

Content	Valence	# of RCs	# of NCs	# of ACs	ASU M	ASU SD	ASU A	Georgia Tech M	Georgia Tech SD	Georgia Tech α	Both M	Both SD	Both A
Intro. to Abnormal Psychology	Pos.	0	2	4	3.81	.99	.89	3.80	1.02	.91	3.80	1.01	.90
Intro. to Abnormal Psychology	Neg.	0	2	4	2.561	.79	.86	2.82	.88	.85	2.72	.85	.86
Intro. to Philosophy	Pos.	0	2	4	3.60	1.01	.92	3.61	.97	.91	3.60	.99	.91
Intro. to Philosophy	Neg.	0	2	4	2.89	.86	.86	3.00	.93	.89	2.95	.90	.88
Religions of the World	Pos.	0	2	4	3.52	1.06	.90	3.42	.94	.88	3.47	1.00	.89
Religions of the World	Neg.	0	2	4	2.92	.90	.85	3.02	1.02	.90	2.98	.97	.88
Intro. to Sociology	Pos.	4	0	2	4.40	.86	.90	4.18	.87	.87	4.28	.87	.88
Intro. to Sociology	Neg.	4	0	2	3.02	.87	.87	3.09	.93	.88	3.06	.90	.87
Intro. to Anthropology	Pos.	4	0	2	3.92	.94	.89	3.91	.92	.90	3.92	.93	.90
Intro. to Anthropology	Neg.	4	0	2	3.21	.87	.85	3.38	.89	.88	3.31	.89	.87
The Global Economy	Pos.	4	0	2	3.50	1.01	.90	3.60	.95	.90	3.56	.98	.90
The Global Economy	Neg.	4	0	2	2.72	.88	.89	2.94	.89	.88	2.84	.89	.89
Intro. to Anthropology (1)	Pos.	2	0	4	3.65	.98	.89	3.63	1.05	.91	3.64	1.02	.90
Intro. to Anthropology (1)	Neg.	2	0	4	2.69	.77	.83	2.72	.93	.89	2.71	.86	.87
Intro. to Anthropology (2)	Pos.	2	0	4	3.51	.98	.91	3.58	.87	.88	3.55	.92	.90
Intro. to Anthropology (2)	Neg.	2	0	4	2.91	.81	.84	3.08	.90	.87	3.00	.86	.86
The Global Economy	Pos.	2	0	4	3.40	1.07	.91	3.41	1.02	.91	3.40	1.04	.91
The Global Economy	Neg.	2	0	4	2.67	.81	.88	2.90	.87	.86	2.79	.85	.87
Intro. to Sociology	Pos.	2	0	4	3.81	.93	.91	3.70	.89	.88	3.75	.91	.90
Intro. to Sociology	Neg.	2	0	4	2.98	.86	.87	2.98	.89	.88	2.98	.87	.87

Note. RCs = rewarding comments, NCs = neutral comments, ACs = aversive comments.

Table 15. Criteria Descriptive Statistics by Rating

Rating	Valence	# of RCs	# of NCs	# of ACs	ASU M	ASU SD	ASU α	Georgia Tech M	Georgia Tech SD	Georgia Tech α	Both M	Both SD	Both α
Rating 1	Pos.	6	0	0	4.41	.70	.93	4.42	.63	.90	4.41	.66	.93
Rating 1	Neg.	6	0	0	3.52	.75	.94	3.86	.68	.92	3.71	.73	.94
Rating 2	Pos.	0	6	0	4.19	.67	.90	4.19	.61	.88	4.19	.63	.90
Rating 2	Neg.	0	6	0	3.46	.68	.92	3.74	.70	.91	3.61	.71	.92
Rating 3	Pos.	0	0	6	3.62	.75	.92	3.49	.70	.90	3.55	.72	.92
Rating 3	Neg.	0	0	6	2.67	.63	.91	2.73	.79	.94	2.70	.72	.91
Rating 4	Pos.	3	3	0	4.18	.67	.91	4.15	.62	.89	4.16	.64	.91
Rating 4	Neg.	3	3	0	3.26	.65	.89	3.45	.67	.91	3.36	.67	.89
Rating 5	Pos.	0	3	3	3.93	.64	.90	3.90	.59	.88	3.91	.61	.90
Rating 5	Neg.	0	3	3	3.12	.66	.92	3.25	.68	.92	3.19	.68	.92
Rating 6	Pos.	3	0	3	4.00	.69	.90	3.94	.59	.87	3.97	.64	.90
Rating 6	Neg.	3	0	3	3.01	.70	.91	3.12	.72	.92	3.07	.71	.91
Rating 7	Pos.	4	2	0	4.35	.79	.93	4.41	.72	.92	4.38	.76	.93
Rating 7	Neg.	4	2	0	3.48	.74	.92	3.83	.72	.90	3.67	.75	.92
Rating 8	Pos.	2	4	0	4.02	.74	.92	4.06	.70	.89	4.04	.72	.92
Rating 8	Neg.	2	4	0	3.26	.67	.90	3.51	.64	.89	3.40	.67	.90
Rating 9	Pos.	0	4	2	3.89	.73	.91	3.93	.69	.89	3.90	.71	.91
Rating 9	Neg.	0	4	2	3.03	.64	.89	3.35	.70	.91	3.20	.70	.89
Rating 10	Pos.	0	2	4	3.65	.79	.91	3.61	.74	.91	3.63	.76	.91
Rating 10	Neg.	0	2	4	2.80	.65	.90	2.95	.75	.92	2.88	.71	.90
Rating 11	Pos.	4	0	2	3.95	.66	.89	3.90	.65	.89	3.92	.65	.89
Rating 11	Neg.	4	0	2	2.98	.63	.89	3.14	.67	.91	3.07	.66	.89
Rating 12	Pos.	2	0	4	3.60	.74	.92	3.57	.72	.91	3.55	.73	.92
Rating 12	Neg.	2	0	4	2.82	.60	.92	2.93	.71	.93	2.88	.66	.92

Note. RCs = rewarding comments, NCs = neutral comments, ACs = aversive comments.

Table 16. Planned Contrasts: Polynomials

			ASU			Georgia Tech			Both		
Content Group	Valence	Planned Comparison	*F*	*p*	η^2	*F*	*p*	η^2	*F*	*p*	η^2
1	Pos.	Linear	195.40	.00	.50	310.76	.00	.57	501.75	.00	.53
1	Neg.	Linear	183.42	.00	.48	383.35	.00	.62	544.98	.00	.56
1	Pos.	Quadratic	28.49	.00	.13	78.13	.00	.25	100.79	.00	.19
1	Neg.	Quadratic	81.06	.00	.29	187.29	.00	.44	254.54	.00	.37
2	Pos.	Linear	34.81	.00	.15	47.98	.00	.17	82.91	.00	.16
2	Neg.	Linear	29.35	.00	.13	65.18	.00	.22	91.89	.00	.17
2	Pos.	Quadratic	41.90	.00	.18	31.23	.00	.12	71.22	.00	.14
2	Neg.	Quadratic	.19	.66	.00	1.08	.30	.01	1.09	.30	.00
3	Pos.	Linear	183.67	.00	.48	300.96	.00	.56	479.44	.00	.52
3	Neg.	Linear	132.26	.00	.45	282.42	.00	.54	438.11	.00	.50
3	Pos.	Quadratic	3.89	.05	.02	.66	.42	.00	3.85	.05	.01
3	Neg.	Quadratic	.02	.88	.00	2.26	.13	.01	1.53	.22	.00
3	Pos.	Cubic	8.31	.00	.04	16.83	.00	.07	25.01	.00	.05
3	Neg.	Cubic	.06	.81	.00	12.56	.00	.05	6.36	.01	.01
4	Pos.	Linear	92.54	.00	.32	102.79	.00	.30	195.69	.00	.31
4	Neg.	Linear	20.08	.00	.09	37.45	.00	.14	57.03	.00	.12

than course descriptions with more aversive comments and less positive comments. The examination of whether the different valences of the comments from the course descriptions resulted in significantly different ratings by participants is a manipulation check. Polynomial contrasts were used to examine Hypothesis 3. As can be seen in Table 16, all linear trends were significant and all produced the expected effect size of $\eta^2 = .10$ or were greater. In addition, four of the six tests with a quadratic trend were also significant. All of the results from the linear trends upheld the predictions made in Hypothesis 3.

An ANOVA was conducted by each rating group to examine the effect of the course content on participants' ratings to compare with the results from the planned contrasts that examined the effect of varying the valence of the comment valence pattern. The ratings were aggregated by course content instead of by pattern of comment valence, which spreads the influence of the comment valence patterns over the course content rating composites. As can be seen in Table 17, all of the models were significant, which indicates that participants rated at least two courses within each rating group significantly different on both the positively- and negatively-toned rating scales. In contrast to the

Table 17. ANOVA by Course Content

		ASU			Georgia Tech			Both		
Content Group	Valence	F	p	η^2	F	p	η^2	F	p	η^2
1	Pos.	4.05	.02	.02	3.42	.03	.01	6.55	.00	.02
1	Neg.	33.61	.00	.15	26.94	.00	.10	59.41	.00	.12
2	Pos.	19.89	.00	.09	3.78	.03	.02	17.85	.00	.04
2	Neg.	18.12	.00	.08	12.70	.00	.05	30.19	.00	.07
3	Pos.	34.53	.00	.15	37.67	.00	.14	71.90	.00	.14
3	Neg.	26.10	.00	.12	45.02	.00	.16	67.44	.00	.13
4	Pos.	46.76	.00	.19	24.75	.00	.09	67.96	.00	.14
4	Neg.	22.32	.00	.10	11.93	.00	.05	31.06	.00	.07

results for the linear effects examined in Hypothesis 3, only half of the effect size estimates fell within the range predicted in Hypothesis 3 ($\eta^2 \geq .10$).

Next, a MANOVA was computed to more directly compare the effect caused by varying the course content versus the comment valence pattern in one model. In this analysis, each positively- and negatively-toned rating scale from each course description was entered separately, except that the four identical course descriptions that were administered to assess test-retest reliability were averaged into one rating score. As can be seen in Table 18, all of the within subjects factors were significant, which indicates that participants rated at least two course descriptions differently because of the different course contents, the different comment valence patterns, and the interaction of the course contents and comment valence patterns. However, the effect size from the comment valence pattern was more likely to fall into the expected effect size range from Hypothesis 3 based on different comment valence patterns than different course contents ($ASU_{\text{course content}}$ = 62.5 percent, average $\eta^2 = .12$, $ASU_{\text{comment valence pattern}}$ = 87.5 percent, average $\eta^2 = .27$; Georgia $Tech_{\text{course content}}$ = 50.0 percent, average $\eta^2 = .08$, Georgia $Tech_{\text{comment valence pattern}}$ = 87.5 percent, average $\eta^2 = .33$).

Hypothesis 4: Predictive Efficiency of the Predictors

It was predicted in the fourth hypothesis that the positively-toned person characteristics (i.e., the BAS scales, the BAS+ scales, Reward Expectancy, and Extraversion) would correlate positively (*r* between .2 and .4) with ratings of course descriptions with appetitive features and that the negatively-toned characteristics (i.e., BIS, BIS+, Punishment Expectancy, and Neuroticism) would correlate negatively (*r* between -.2 and -.4) with ratings of course descriptions with aversive features. As the

Table 18. MANOVA by Course Content and Comment Pattern Valence

Content Group	Valence	WSF	ASU *F*	ASU *p*	ASU η^2	Georgia Tech *F*	Georgia Tech *p*	Georgia Tech η^2	Both *F*	Both *p*	Both η^2
1	Pos.	Content	4.17	.02	.02	3.42	.03	.01	6.35	.00	.01
1	Pos.	Valence	146.4	.00	.43	249.08	.00	.51	390.70	.00	.48
1	Pos.	Interaction	8.42	.00	.04	17.42	.00	.07	24.56	.00	.05
1	Neg.	Content	33.44	.00	.15	27.36	.00	.10	59.53	.00	.12
1	Neg.	Valence	152.09	.00	.44	327.61	.00	.58	461.46	.00	.52
1	Neg.	Interaction	12.95	.00	.06	28.14	.00	.11	38.47	.00	.08
2	Pos.	Content	19.41	.00	.09	3.65	.03	.02	17.31	.00	.04
2	Pos.	Valence	38.95	.00	.17	41.76	.00	.15	80.10	.00	.16
2	Pos.	Interaction	18.03	.00	.09	18.30	.00	.07	34.84	.00	.07
2	Neg.	Content	18.34	.00	.09	12.52	.00	.05	30.16	.00	.07
2	Neg.	Valence	17.00	.00	.08	43.46	.00	.15	57.78	.00	.12
2	Neg.	Interaction	27.34	.00	.12	62.65	.00	.21	86.59	.00	.17
3	Pos.	Content	35.63	.00	.16	36.31	.00	.13	71.52	.00	.14
3	Pos.	Valence	104.89	.00	.35	162.98	.00	.41	266.18	.00	.38
3	Pos.	Interaction	7.75	.00	.04	8.87	.00	.04	16.19	.00	.04
3	Neg.	Content	26.58	.00	.12	44.16	.00	.16	67.76	.00	.14
3	Neg.	Valence	88.06	.00	.31	148.96	.00	.39	233.50	.00	.35
3	Neg.	Interaction	35.89	.00	.16	59.40	.00	.20	94.18	.00	.18
4	Neg.	Content	45.82	.00	.19	24.42	.00	.09	66.74	.00	.13
4	Neg.	Valence	88.57	.00	.31	101.01	.00	.30	189.95	.00	.31
4	Neg.	Interaction	17.31	.00	.08	8.94	.00	.04	25.53	.00	.06
4	Pos.	Content	22.97	.00	.11	11.85	.00	.05	31.26	.00	.07
4	Pos.	Valence	21.86	.00	.10	37.78	.00	.14	59.39	.00	.12
4	Pos.	Interaction	11.65	.00	.06	16.22	.00	.06	27.83	.00	.06

Note. WSF = Within subjects factor.

ratings bifurcated into positive and negative scales, the effects were more likely to hold when the valence was consistent (i.e., positively-toned characteristics significantly predicting positively-toned ratings for course descriptions with appetitive features, negatively-toned characteristics significantly predicting negatively-toned ratings for course descriptions with aversive features). Table 19 and Table 20 display the correlations of the positively- and negatively-toned characteristics with the positively-toned and negatively-toned ratings. None of the correlations exceeded the predicted range ($r > .4$); all of the correlations were either within the predicted range (r between .2 and .4) or below the predicted range ($r < .2$). Table 21 summarizes the statistics reported

Table 19. Correlation between Predictors and Positively-Toned Ratings

	Rating 1	Rating 2	Rating 3	Rating 4	Rating 5	Rating 6	Rating 7	Rating 8	Rating 9	Rating 10	Rating 11	Rating 12
	R[1] N[2] A[3]	R N A	R N A	R N A	R N A	R N A	R N A	R N A	R N A	R N A	R N A	R N A
	6 0 0	0 6 0	0 0 6	3 3 0	0 3 3	3 0 3	4 2 0	2 4 0	0 4 2	0 2 4	4 0 2	2 0 4
ASU												
BIS	.16*	.15*	.02	.12	.10	.13	.21*	.21*	.18*	.13	.11	-.04
BAS	.19*	.12	.07	.16*	.18*	.23*	.12	.14	.05	.07	.14	.05
BAS-Fun	.17*	.11	.13	.15*	.17*	.22*	.11	.09	.02	.06	.12	.11
BAS-RR	.23*	.15*	.02	.20*	.23*	.25*	.22*	.20*	.14*	.11	.13	-.01
BAS-Drive	.05	.03	.01	.02	.01	.06	-.04	.03	-.04	.00	.07	.02
BIS+	.04	.07	-.07	.02	.03	.02	.09	.12	.08	.03	.00	-.14
BAS+	.33*	.24*	.11	.28*	.27*	.30*	.28*	.27*	.17*	.19*	.26*	.13
BAS-Fun+	.26*	.20*	.12	.23*	.22*	.26*	.19*	.15*	.09	.09	.20*	.14
BAS-RR+	.27*	.16*	.00	.20*	.19*	.21*	.23*	.21*	.10	.09	.12	-.01
BAS-Drive+	.24*	.20*	.16*	.23*	.23*	.26*	.22*	.27*	.20*	.27*	.30*	.19*
RE	.39*	.36*	.23*	.31*	.28*	.36*	.30*	.24*	.20*	.27*	.36*	.34*
PE	-.11	-.06	-.16*	-.06	-.08	-.11	-.10	-.06	.00	-.07	-.10	-.19*
Neuroticism	-.07	-.05	-.09	-.08	-.02	-.07	-.01	.01	-.01	-.03	-.08	-.18*
Extraversion	.25*	.28*	.11	.22*	.16*	.24*	.19*	.20*	.08	.16*	.18*	.17*
Georgia Tech												
BIS	.08	.06	-.10	.02	-.06	-.06	.09	.08	.01	.00	.00	-.06
BAS	.15*	.20*	.09	.06	.09	.11	.05	.01	.02	.02	.06	.15*
BAS-Fun	.02	.07	.09	.03	.08	.08	.04	-.01	.03	.02	-.01	.13*
BAS-RR	.23*	.22*	-.02	.10	.03	.07	.06	.01	-.03	-.10	.03	.02
BAS-Drive	.09	.14*	.10	.01	.07	.09	.02	.01	.04	.08	.10	.15*
BIS+	.00	.00	-.13*	-.07	-.12	-.14*	.04	.02	-.02	-.03	-.05	-.11
BAS+	.24*	.28*	.17*	.14*	.15*	.15*	.15*	.11	.10	.09	.12	.21*
BAS-Fun+	.10	.13*	.13*	.07	.10	.12	.11	.06	.04	.05	.07	.15*
BAS-RR+	.22*	.27*	.04	.09	.03	.04	.09	.06	.05	-.04	.01	.01
BAS-Drive+	.23*	.25*	.22*	.17*	.21*	.18*	.14*	.14*	.16*	.20*	.20*	.32*
RE	.21*	.22*	.24*	.18*	.17*	.20*	.08	.11	.10	.14*	.20*	.24*

Table 19 (continued).

	Rating 1	Rating 2	Rating 3	Rating 4	Rating 5	Rating 6	Rating 7	Rating 8	Rating 9	Rating 10	Rating 11	Rating 12
	R N A	R N A	R N A	R N A	R N A	R N A	R N A	R N A	R N A	R N A	R N A	R N A
	6 0 0	0 6 0	0 0 6	3 3 0	0 3 3	3 0 3	4 2 0	2 4 0	0 4 2	0 2 4	4 0 2	2 0 4
PE	-.01	.03	-.07	-.01	-.03	-.06	-.02	-.02	-.10	-.02	-.03	-.05
Neuroticism	-.08	-.03	-.17*	-.12	-.18*	-.18*	-.03	-.02	-.07	-.06	-.10	-.16*
Extraversion	.15*	.14*	.14*	.09	.07	.20*	.23*	.17*	.12	.13*	.11	.19*
						Both						
BIS	.12*	.10*	-.06	.06	.01	.03	.15*	.14*	.09	.06	.04	-.05*
BAS	.17*	.16*	.09	.11*	.13*	.18*	.08	.07	.03	.05	.10*	.10*
BAS-Fun	.09	.09	.12*	.09	.13*	.15*	.06	.04	.02	.04	.06	.12*
BAS-RR	.23*	.18*	.00	.15*	.13*	.17*	.14*	.10*	.05	.01	.08	.00
BAS-Drive	.07	.09	.06	.02	.05	.08	-.01	.02	.00	.05	.08	.09
BIS+	.02	.03	-.11*	-.03	-.05	-.07	.06	.06	.02	-.01	-.04	-.12*
BAS+	.28*	.26*	.15*	.21*	.21*	.23*	.21*	.19*	.13*	.14*	.19*	.17*
BAS-Fun+	.17*	.16*	.14*	.15*	.16*	.19*	.14*	.10*	.06	.07	.14*	.14*
BAS-RR+	.24*	.22*	.03	.14*	.11*	.12*	.16*	.13*	.07	.02	.06	.00
BAS-Drive+	.23*	.22*	.19*	.20*	.22*	.22*	.17*	.20*	.18*	.23*	.25*	.26*
RE	.29*	.29*	.24*	.24*	.22*	.28*	.18*	.17*	.14*	.20*	.27*	.28*
PE	-.06	-.01	-.11*	-.04	-.05	-.09	-.06	-.04	-.05	-.04	-.06	-.12*
Neuroticism	-.07	-.04	-.13*	-.11*	-.11*	-.13*	-.02	-.01	-.05	-.05	-.09	-.17*
Extraversion	.19*	.20*	.14*	.15*	.11*	.22*	.20*	.18*	.10*	.15*	.15*	.19*

Note. [1]R = Reward, [2]N = Neutral, [3]A = Aversive, BAS-RR = BAS Reward Responsiveness, PE = Punishment Expectancy, RE = Reward Expectancy.
$*p < .05$.

Table 20. Correlation between Predictors and Negatively-Toned Ratings

	Rating 1	Rating 2	Rating 3	Rating 4	Rating 5	Rating 6	Rating 7	Rating 8	Rating 9	Rating 10	Rating 11	Rating 12
	R[1] N[2] A[3]	R N A	R N A	R N A	R N A	R N A	R N A	R N A	R N A	R N A	R N A	R N A
	6 0 0	0 6 0	0 0 6	3 3 0	0 3 3	3 0 3	4 2 0	2 4 0	0 4 2	0 2 4	4 0 2	2 0 4
ASU												
BIS	-.12	-.15*	-.25*	-.16*	-.17*	-.17*	-.14*	-.21*	-.25*	-.26*	-.16*	-.25*
BAS	.06	.00	-.04	.08	.04	-.08	.02	.02	-.04	-.02	-.01	-.07
BAS-Fun	.10	.03	.07	.10	.15*	.03	.04	.12	.06	.10	.05	.08
BAS-RR	.02	-.02	-.18*	.02	-.06	-.17*	.01	-.10	-.10	-.15*	-.10	-.19*
BAS-Drive	.02	.00	.01	.05	.00	-.06	-.01	.02	-.06	.00	.02	-.06
BIS+	-.10	-.10	-.18*	-.14*	-.13	-.16*	-.15	-.20*	-.21*	-.21*	-.16*	-.21*
BAS+	.09	.02	-.12	.03	-.02	-.16*	.02	-.01	-.05	-.13	-.09	-.14*
BAS-Fun+	.11	.03	.02	.06	.09	-.04	.00	.09	.04	.04	.00	.03
BAS-RR+	.08	.03	-.17*	.02	-.08	-.20*	.04	-.05	-.07	-.22*	-.15*	-.22*
BAS-Drive+	.04	.03	-.10	.02	-.02	-.11	.02	-.06	-.09	-.11	-.03	-.14
RE	.17*	.19*	.09	.18*	.09	.10	.14*	.19*	.09	.04	.08	.12
PE	-.07	-.13	-.04	-.08	-.05	-.10	-.07	-.17*	.00	-.06	-.05	-.09
Neuroticism	-.10	-.11	-.10	-.13	-.09	-.11	-.11	-.21*	-.13	-.14*	-.12	-.17*
Extraversion	.07	.07	.10	.10	.05	.03	.05	.15*	.07	.02	.01	.08
Georgia Tech												
BIS	-.11	-.15*	-.20*	-.14*	-.22*	-.20*	-.17*	-.18*	-.19*	-.24*	-.21*	-.22*
BAS	-.03	.01	.01	.01	-.05	-.05	-.05	-.02	-.04	.06	-.03	.02
BAS-Fun	-.05	-.04	.00	.01	-.01	-.05	-.04	-.04	-.05	.05	-.05	.04
BAS-RR	.06	.05	-.08	.03	-.12	-.12	.02	-.01	-.02	-.03	-.07	-.04
BAS-Drive	-.05	.02	.07	-.02	.01	.04	-.08	.00	-.02	.08	.04	.02
BIS+	-.16*	-.22*	-.21*	-.21*	-.26*	-.22*	-.21*	-.23*	-.19*	-.24*	-.25*	-.26*
BAS+	.01	.07	.00	.01	-.02	-.04	-.03	-.02	-.04	.05	-.08	.02
BAS-Fun+	-.01	.02	.04	.03	.06	-.02	-.02	-.01	-.03	.10	-.04	.08
BAS-RR+	.01	.05	-.05	-.01	-.07	-.11	-.02	-.03	-.04	-.03	-.09	-.07
BAS-Drive+	.04	.14*	.06	.04	.00	.07	.01	.03	.01	.07	.01	.08
RE	.11	.25*	.19*	.20*	.15*	.18*	.13*	.14*	.17*	.20*	.14*	.24*

Table 20 (continued).

	Rating 1	Rating 2	Rating 3	Rating 4	Rating 5	Rating 6	Rating 7	Rating 8	Rating 9	Rating 10	Rating 11	Rating 12
	R N A	R N A	R N A	R N A	R N A	R N A	R N A	R N A	R N A	R N A	R N A	R N A
	6 0 0	0 6 0	0 0 6	3 3 0	0 3 3	3 0 3	4 2 0	2 4 0	0 4 2	0 2 4	4 0 2	2 0 4
PE	-.13*	-.08	-.03	-.11	-.11	-.11	-.12	-.09	-.12	-.05	-.10	-.05
Neuroticism	-.17*	-.22*	-.20*	-.19*	-.27*	-.22*	-.21*	-.25*	-.21*	-.23*	-.22*	-.27*
Extraversion	-.02	.01	.06	-.07	-.03	.01	.00	-.04	-.05	.03	-.08	.10
						Both						
BIS	-.09	-.13*	-.21*	-.13*	-.19*	-.18*	-.13*	-.17*	-.19*	-.24*	-.18*	-.22*
BAS	-.01	-.02	-.02	.02	-.02	-.07	-.05	-.02	-.07	.01	-.04	-.03
BAS-Fun	-.01	-.04	.02	.03	.04	-.02	-.04	.00	-.04	.05	-.03	.05
BAS-RR	.02	.01	-.12*	.02	-.10*	-.15*	.00	-.06	-.07	-.09	-.09	-.11*
BAS-Drive	-.03	.00	.04	.00	.00	-.01	-.06	.00	-.05	.04	.02	-.02
BIS+	-.12*	-.15*	-.20*	-.17*	-.20*	-.19*	-.16*	-.20*	-.18*	-.22*	-.20*	-.23*
BAS+	.02	.02	-.05	.00	-.03	-.10*	-.04	-.04	-.08	-.04	-.10*	-.06
BAS-Fun+	.01	-.01	.02	.02	.06	-.04	-.05	.01	-.03	.06	-.04	.04
BAS-RR+	.03	.03	-.10*	-.01	-.08	-.15*	-.01	-.05	-.06	-.12*	-.12*	-.14*
BAS-Drive+	.03	.08	.00	.02	-.02	-.01	.00	-.02	-.04	-.01	-.02	-.01
RE	.12*	.20*	.15*	.18*	.12*	.14*	.11	.15*	.11*	.13*	.10*	.18*
PE	-.10*	-.10*	-.03	-.10*	-.08	-.10*	-.09	-.13	-.06	-.05	-.08	-.07
Neuroticism	-.13*	-.18*	-.17*	-.17*	-.20*	-.18*	-.16*	-.22*	-.18*	-.20*	-.18*	-.24*
Extraversion	-.01	.00	.07	-.02	-.01	.00	-.02	.01	-.04	.01	-.06	.08

Note. [1]R = Reward, [2]N = Neutral, [3]A = Aversive, BAS-RR = BAS Reward Responsiveness, PE = Punishment Expectancy, RE = Reward Expectancy.
**p* < .05.

in Table 19 and Table 20 for the ASU and Georgia Tech samples. Table 21 reports the frequency with which a correlation met the expectations expressed in the fourth hypothesis (*r* with an effect size between .2 and .4) as well as the average correlation. Seven of the ratings included appetitive comments and seven of the ratings included aversive comments. The hypothesized ratings are the seven ratings that included course descriptions with at least one comment of the same valence as the predictor.

For the positively-toned characteristics and the ASU sample, seven of the predictors fell within the predicted range of effects sizes with 50 percent or more of the ratings that included at least one positively-toned comments (i.e., the hypothesized ratings) and five of the predictors fell within the predicted range of effects sizes with 50 percent or more of the ratings across all of the ratings. Two of the negatively-toned predictors fell within the predicted range of effects sizes with 50 percent or more of the ratings that included at least one negatively-toned comment and across all of the ratings. For the positively-toned characteristics and the Georgia Tech sample, one of the predictors fell within the predicted range of effects sizes with 50 percent or more of the ratings that included at least one positively-toned comment (i.e., the hypothesized ratings) and one of the predictors fell within the predicted range of effects sizes with 50 percent or more of the ratings across all of the comments. For the Georgia Tech sample, all but one of the predictors fell within the predicted range of effects sizes with 50 percent or more of the negatively-toned ratings for the ratings that included at least one negatively-toned comment (i.e., the hypothesized ratings) and across all of the ratings.

Turning to the average correlations reported in Table 21, for the ASU sample, on average, BAS+ ($r_{\text{hypothesized ratings}} = .26$, $r_{all\ ratings} = .24$), BAS-Fun+ ($r_{\text{hypothesized ratings}} = .20$,

$r_{all\ ratings}$ = .18), BAS-Drive+ ($r_{\text{hypothesized ratings}}$ = .24, $r_{all\ ratings}$ = .23), Reward Expectancy ($r_{\text{hypothesized ratings}}$ = .33, $r_{all\ ratings}$ = .30), and Extraversion ($r_{\text{hypothesized ratings}}$ = .21, $r_{all\ ratings}$ = .19) fell within the hypothesized range of effect sizes (*r* between .2 and .4); however, these results did not generalize to the Georgia Tech sample with just BAS-Drive+ ($r_{\text{hypothesized ratings}}$ = .20, $r_{all\ ratings}$ = .20) falling into the expected range. For the Georgia Tech sample, on average, BIS ($r_{\text{hypothesized ratings}}$ = -.21, $r_{all\ ratings}$ = -.19), BIS+ ($r_{\text{hypothesized ratings}}$ = -.23, $r_{all\ ratings}$ = -.22), and Neuroticism ($r_{\text{hypothesized ratings}}$ = -.23, $r_{all\ ratings}$ = -.22) fell within the hypothesized range of effect sizes (*r* between -.2 and -.4); however, these results did not generalize to the ASU sample with just BIS ($r_{\text{hypothesized ratings}}$ = -.22, $r_{all\ ratings}$ = -.19) falling into the expected range. In summary, support for Hypothesis 4 appears somewhat mixed as the results only partially generalize from one sample to the other sample.

Table 21. Summary of Correlation Results

	ASU				Georgia Tech			
	Hypothesized Ratings		All Ratings		Hypothesized Ratings		All Ratings	
Predictors	%	$\bar{r}$	%	$\bar{r}$	%	$\bar{r}$	%	$\bar{r}$
			Positively-Toned Ratings					
BAS	14%	.15	8%	.13	0%	.08	8%	.08
BAS-Fun	14%	.14	8%	.12	0%	.04	0%	.05
BAS-RR	71%	.17	50%	.16	14%	.07	17%	.05
BAS-Drive	0%	.03	0%	.02	0%	.07	0%	.08
BAS+	86%	.26	67%	.24	14%	.16	17%	.16
BAS-Fun+	57%	.20	50%	.18	0%	.10	0%	.09
BAS-RR+	71%	.18	42%	.15	14%	.07	17%	.07
BAS-Drive+	86%	.24	83%	.23	43%	.20	58%	.20
RE	100%	.33	100%	.30	57%	.17	42%	.17
Extraversion	57%	.21	42%	.19	29%	.16	17%	.15
Average	56%	.19	45%	.17	17%	.11	18%	.11
			Negatively-Toned Ratings					
BIS	71%	-.22	75%	-.19	86%	-.21	50%	-.19
BIS+	86%	-.18	75%	-.16	86%	-.23	83%	-.22
PE	14%	-.06	25%	-.08	0%	-.08	0%	-.09
Neuroticism	0%	-.12	0%	-.13	100%	-.23	83%	-.22
Average	43%	-.14	33%	-.14	68%	-.19	54%	-.18

However, a variety of comment valence patterns were used to provide a variety of task conditions for the study. Although support for Hypothesis 4 appears a little mixed when averaging ratings, another set of analyses was conducted using the ratings most likely to support Hypothesis 4 based on Reward Sensitivity Theory (Gray, 1987, 1994; Gray et al., 1983; Pickering et al., 1995; Pickering & Gray, 1999). Based on Reward Sensitivity Theory, the rating most likely to support Hypothesis 4 for the negatively-toned characteristics is Rating 3 (negatively toned), as it contains all negatively-valenced comments, and the rating most likely to support Hypothesis 4 for the positively-toned characteristics is Rating 1 (positively toned), as it contains all positively-valenced comments. As before, the effect size for only one predictor, BIS (r = -.25), fell within the expected range of effect sizes with the ASU sample. With the Georgia Tech sample, BIS (r = -.20), BIS+ (r = -.21), and Neuroticism (r = -.20) fell within the predicted range of effect sizes (r between -.2 and -.4). The following positively-toned characteristics fell within the predicted effect size range (r between -.2 and -.4) when correlated with Rating 1 (positively toned) in both samples: BAS-Reward Responsiveness ($\bar{r}$ = .23), BAS+ ($\bar{r}$ = .28), BAS- Reward Responsiveness+ ($\bar{r}$ = .24), BAS-Drive+ ($\bar{r}$ = .23), and Reward Expectancy ($\bar{r}$ = .29). When examining the predictions made in Hypothesis 4 with just the two ratings most likely to support expectations the results remained somewhat mixed for the negatively-toned predictors with just one of the four predictors falling into the expected range of effect sizes in both samples, but provided more consistent support for predictions with the positively-toned predictors.

Several additional analyses were conducted to determine the congruence between data collected from the ASU and Georgia Tech samples. First, confidence intervals were computed for the correlations between the predictors and ratings. The confidence interval for all of the corresponding correlation between ASU and Georgia Tech for each predictor and rating comparison overlapped, which suggests that the correlations across the two samples were not significantly different.

Next, ratings of ASU and Georgia Tech professors on ratemyprofessors.com were compared to determine whether students from the schools rated their professors differently (Rate My Professors, n.d.). As both samples came from psychology subject pools, only professors listed in ASU's Department of Psychology and Georgia Tech's School of Psychology were compared. To avoid problems with lack of independence, the ratings from each professor were averaged first. Ratings were obtained for overall quality (ASU: M = 3.72, SD = 1.15; Georgia Tech: M = 3.73, SD = 1.05) and ease (ASU: M = 3.19, SD = 1.32; Georgia Tech: M = 3.07, SD = .92). A t-test revealed no significant difference for either overall quality, $t(134) = -.043$, $p < .05$, or ease, $t(134) = .465$, $p < .05$, which does not support a difference in terms of how students from ASU and Georgia Tech rate their psychology professors. These additional analyses indicate that the difference between the correlations between the ASU and Georgia Tech samples was not significantly different and that, based on the ratings from ratemyprofessors.com, a difference would not be expected.

Hypothesis 5: Interaction Effects

Moderated regressions. The expectations expressed in the fifth hypothesis predicted that an interaction between the negatively- and positively-toned characteristics would significantly predict course ratings. As the amount of power associated with detecting an interaction effect is low (McClelland & Judd, 1993), any significant effect was interpreted as support for the hypothesis. The multiple regression analyses allow for a comparison of the predictive efficiency of each negatively- and positively-toned characteristic pair (i.e., BIS/BAS, BIS+/BAS+, Punishment Expectancy/Reward Expectancy, and Neuroticism/Extraversion) entered simultaneously into a multiple regression and the influence of adding an interaction term between the negatively- and positively-toned characteristics in a second step of the model. Procedures for conducting a moderated regression, including centering, described by McLelland and Judd (1993) were followed. The regressions allow for an examination of the joint subsystems hypothesis—the extent to which the behavioral inhibition system and the behavioral activation system have a joint influence on outcomes (Corr, 2001).

For the ASU sample and the positively-toned ratings, the interaction term was significant for two ratings with BIS/BAS, for one rating with BIS+/BAS+, and for one rating with Neuroticism/Extraversion. For the ASU sample and the negatively-toned ratings, the interaction term was significant for one rating with BIS/BAS and BIS+/BAS+. For the Georgia Tech sample and the positively-toned ratings, the interaction term was of significant for three ratings with BIS/BAS and for ten ratings with BIS+/BAS+. For the Georgia Tech sample and the negatively-toned ratings, the interaction term was significant for two ratings with BIS/BAS. In summary, across 192 moderated regressions the interaction term was significant in 23 of the models (12 percent of the models). The analyses support the need to investigate for an interaction effect as posited by Corr (2001) in the joint subsystems hypothesis; however, just 12 percent of the models supported an interaction effect.

Interaction plots. To examine whether the nature of the interaction effects found between the negatively- and positively-toned characteristics conformed to predictions made in Hypothesis 5 and by Corr (2001) in the joint subsystems hypothesis, plots were computed whenever an interaction term was significant (see Appendix A). Consistent with the joint subsystems hypothesis, it was predicted in the fifth hypothesis that as the level of one subsystem increased the effect of the other subsystem would be inhibited. Accordingly, the influence of the behavioral inhibition system on the negatively-toned ratings should decrease as the level of the behavioral activation system increases, and the influence of the behavioral activation system on the positively-toned ratings should decrease as the level of the behavioral inhibition system increases. The plots allow for a more thorough evaluation of Corr's addition to the Reward Sensitivity Theory and may reveal why past study results have not conformed to predictions made in the joint subsystems hypothesis.

As with past studies (Corr, 2002; Jackson & Francis, 2004; Kambouropoulos & Staiger, 2004; see also Zinbarg and Revelle, 1989), the nature of the interactions was inconsistent and varied by sample and predictor pair. Furthermore, the nature of the interaction was often inconsistent with expectations from the joint subsystems hypothesis (Corr, 2001). Although the results support the presence of interaction effects and, thus, the need to look for interactions, the findings do little to advance our understanding of the nature of the interaction effect between negatively- and positively-toned characteristics.

<u>Hypothesis 6: Multilevel Modeling Analyses</u>

Finally, the effect of BIS and BAS sensitivity was examined in a model that also included the effect of the task condition for each group of course descriptions. It was predicted in Hypotheses 6a and 6b that the negatively- and positively-toned characteristics would remain significant predictors in models that also included the task condition in the model, and it was predicted in Hypotheses 6c and 6d that the cross-level interaction between the positively- and negatively-toned characteristics and the task conditions would be significant predictors in models that also included the task conditions. Table 22 displays the intercepts-only models and the models with the Level 1 predictors (dummy codes for the task condition) included. Level 2 predictors (negatively-toned characteristics, positively-toned characteristics, and their interaction) were added to the models in Table 23 through Table 26. As described below, it is necessary to interpret the results from the lower level models (i.e., intercepts-only models, models with Level 1 predictors added) presented in Table 22 to provide a fuller understanding of the models presented in Table 23 through Table 26 (i.e., models with Level 2 predictors added). Next, Table 27 through Table 30 display the multilevel models with the cross-level interaction terms (interactions between the dummy codes for the task condition and the negatively- and positively-toned characteristics) added.

Procedures for conducting multilevel modeling analyses in SPSS described by Peugh and Enders (2005) were followed. As the purpose of the multilevel modeling analyses was to determine the predictive efficiency of Level 2 predictors above and beyond Level 1 predictors, grand mean centering was used for both the Level 1 and Level 2 predictors (see Enders & Tofighi, 2007). A model building approach based on Hox's (1995) steps was used to construct each model (see also Raudenbush & Bryk, 2002). The starting point was the simplest model with no predictors, the intercepts-only model. Next, all Level 1 predictors were entered into the model individually as fixed parameters (their slopes were not permitted to vary). In an iterative procedure, each variable that resulted in a significant improvement in model fit was retained in order of the variable that resulted in the greatest improvement in fit. Next, the contribution of each variable as a random parameter (slopes permitted to vary) was assessed on a similar one-by-one basis. Next, the Level 2 predictors were entered into the model using the same procedure as used with the Level 1 predictors. And finally, the inclusion of the cross-level interaction terms was tested using a similar procedure as the Level 1 and Level 2 predictors. If the cross-level interaction term was significant, then both direct effects were included in the model even if they were not significant.

The change in -2LL (or deviance) was used to compute χ^2 nested model tests to determine whether model improvement was significant (Hox, 1995; Raudenbush & Bryk, 2002). In addition, a model was considered untenable if convergence was not reached in 500 iterations. Lack of convergence typically indicates model misspecification. Alternatively, the sample size may not be sufficient. Full maximum likelihood estimation was used instead of restricted maximum likelihood as nested model tests were conducted with both fixed and random effects (Hox, 1995; Raudenbush & Bryk, 2002). In addition, the Level 1 (σ^2) variance should decrease when meaningful Level 1 predictors are added, and the Level 2 variance (τ_{00}) should decrease when meaningful Level 2 predictors are added. The variance/covariance structure was left unstructured. The results from the Wald test for the variance components were not reported due to questions regarding the validity of this test. As different samples were compared, unstandardized coefficients were used (see Hox, 1995).

Intercepts-only models. The intercepts-only models allow for an assessment of

Table 22. Multilevel Modeling Analyses: Intercepts-Only Models and Level 1 Predictors-Only Models

	Intercepts-Only Models				Level 1 Predictors-Only Models					
Rating Group	ICC	σ^2	τ_{00}	-2LL	R_1	R_2	R_3	σ^2	τ_{00}	-2LL
ASU										
Group 1 (Pos.)	.361	.39	.22	1,324.0	.22*	-.56*	--	.11	.31	1,050.4
Group 2 (Pos.)	.761	.11	.35	834.2	.26*	.07*	--	.09	.35	764.1
Group 3 (Pos.)	.615	.25	.40	1,553.1	.47*	.14*	-.23*	.11	.43	1,273.0
Group 4 (Pos.)	.627	.19	.32	765.5	.35*	--	--	.13	.35	689.2
Group 1 (Neg.)	.145	.53	.09	1,398.7		-.82*	--	.17	.21	1,115.9
Group 2 (Neg.)	.578	.19	.26	1,029.9	.14*	-.11*	--	.15	.28	988.0
Group 3 (Neg.)	.462	.28	.24	1,545.7	.45*	.24*	-.23*	.12	.28	1,293.3
Group 4 (Neg.)	.615	.15	.24	655.1	.17*	--	--	.13	.24	635.9
Georgia Tech										
Group 1 (Pos.)	.193	.46	.11	1,611.7	.22*	-.71*	--	.11	.23	1,192.3
Group 2 (Pos.)	.676	.12	.25	1,003.4	.23*		--	.09	.26	921.0
Group 3 (Pos.)	.542	.27	.32	1,868.2	.42*	-.38*		.16	.35	1,503.6
Group 4 (Pos.)	.633	.18	.31	895.4	.33*	--	--	.13	.34	809.6
Group 1 (Neg.)	.141	.67	.11	1,841.3	.12*	-1.01*	--	.13	.29	1,341.7
Group 2 (Neg.)	.633	.18	.31	1,248.3	.19*	-.14*	--	.11	.34	1,145.1
Group 3 (Neg.)	.407	.35	.24	2,026.9	.40*		-.48*	.17	.29	1,661.1
Group 4 (Neg.)	.667	.16	.32	872.5	.21*	--	--	.14	.33	837.6
Both										
Group 1 (Pos.)	.271	.43	.16	2,943.1	.23*	-.64*	--	.11	.27	2,251.6
Group 2 (Pos.)	.707	.12	.29	1,844.8	.25*	.05*	--	.08	.30	1,691.4
Group 3 (Pos.)	.581	.26	.36	3,423.9	.47*	.13*	-.28*	.16	.38	2,794.6
Group 4 (Pos.)	.627	.19	.32	1,661.6	.34*	--	--	.13	.34	1,499.5
Group 1 (Neg.)	.167	.60	.12	3,266.3	.09*	-.91*	--	.15	.27	2,511.4
Group 2 (Neg.)	.604	.19	.29	2,285.5	.17*	-.13	--	.13	.31	2,147.6
Group 3 (Neg.)	.448	.32	.26	3,603.3	.47*	.20*	-.32*	.17	.30	2,992.8
Group 4 (Neg.)	.644	.16	.29	1,537.1	.19*	--	--	.14	.29	1,483.4

Note. R = dummy codes for ratings, R_1: (Group 1 = Rating 1, Group 2 = Rating 4, Group 3 = Rating 7, Group 4 = Rating 11), R_2: (Group 1 = Rating 3, Group 2 = Rating 6, Group 3 = Rating 8), R_3: (Group 3 = Rating 10). Slopes of parameters allowed to vary across ratings are underlined.
*p < .05.

the amount of variability that exists between Level 2 units (i.e., participants), whether the use of multilevel modeling is warranted, and whether the addition of Level 1 and Level 2 predictors is warranted (see Table 22; Hox, 1995; Raudenbush & Bryk, 2002). The presence of variance at Level 1 (σ^2 varied from .09 to .67) and at Level 2 (τ_{00} varied from .11 to .53) indicated that multilevel modeling was warranted and that the addition of Level 1 and Level 2 predictors was also warranted (cf. Hox, 1995; Raudenbush & Bryk, 2002). In addition, the intraclass correlation coefficients varied from .14 to .76 indicating that between 14 to 76 percent of the rating variance occurred between participants, which supports the decision to use a multilevel modeling approach and the introduction of Level 2 predictors.

Level 1 predictors added. The Level 1 predictors were entered into the model and tested next (see Table 22). The Level 1 predictors are dummy coded variables that represent specific task conditions for each of the four rating groups (Group 1: Rating 1 and Rating 3; Group 2: Rating 4 and Rating 6; Group 3: Rating 7, Rating 8, and Rating 10; Group 4: Rating 11). The addition of the Level 1 predictors significantly improved model fit in every model, and every model included at least one significant Level 1 fixed effect. Allowing the slopes of one Level 1 predictor to vary among participants further improved fit in 63 percent of the models for both the ASU and Georgia Tech samples. The addition of the Level 1 predictors was also associated with a decrease in the amount of Level 1 variance (ASU sample: $\bar{\sigma}^2$ Intercepts-Only Models = .26, $\bar{\sigma}^2$ with Level 1 Predictors = .13, $\Delta\bar{\sigma}^2$ = .14; Georgia Tech sample: $\bar{\sigma}^2$ Intercepts-Only Models = .30, $\bar{\sigma}^2$ with Level 1 Predictors = .13, $\Delta\bar{\sigma}^2$ = .17).

Level 2 predictors added. As the intercepts-only models supported the addition of

Level 2 predictors, another set of multilevel modeling analyses was computed to assess the predictions made in the sixth hypothesis regarding the addition of the negatively- and positively-toned characteristics (i.e., the Level 2 predictors). The results from the models with the Level 2 predictors added may be compared to the results obtained from the models with the Level 1 predictors added to evaluate the differences in the models. It was predicted in Hypotheses 6a and 6b that the negatively- and positively-toned characteristics would be significant predictors in models that also included the course description conditions, that the addition of Level 2 predictors would improve the fit of 50 percent or more of the models, and of those models, 50 percent or more would include a significant Level 2 fixed effect (see Table 23 through Table 26). In addition, the amount of Level 2 variance should decrease by $\tau_{00} = .02$ or greater. Results were not reported if there was no combination of Level 2 predictors that significantly improved model fit.

For the ASU sample, adding the Level 2 predictors significantly improved the fit of 97 percent of the models. Of the 31 models that the Level 2 predictors significantly improved fit, 27 included a Level 2 predictor with a significant fixed effect (87 percent). The inclusion of the Level 2 variables also caused a reduction in the amount of Level 2 variance present in the models ($\bar{\tau}_{00\ \text{with Level 1 predictors}} = .31$, $\bar{\tau}_{00\ \text{with Level 1 and Level 2 predictors}} = .28$, $\Delta\bar{\tau}_{00} = .02$).

For the Georgia Tech sample, adding Level 2 predictors significantly improved the fit of 94 percent of the models. Of the 30 models that the Level 2 predictors significantly improved fit, all thirty included a Level 2 predictor with a significant fixed effect. The inclusion of the Level 2 variables also caused a reduction in the amount of

Table 23. Multilevel Modeling Analyses with Level 1 and Level 2 Predictors (BIS/BAS)

Rating Group	R_1	R_2	R_3	BIS	BAS	Inter.	σ^2	τ_{00}	-2LL
				ASU					
Group 1 (Pos.)	.22*	<u>-.56</u>*	--		.18*		.11	.30	1,045.8
Group 2 (Pos.)	.25*	.07*	--		.25*		.09	.34	755.9
Group 3 (Pos.)	<u>.47</u>*	.14*	<u>-.23</u>*	.18*			.11	.42	1,264.6
Group 4 (Pos.)		--	--						
Group 1 (Neg.)		<u>-.82</u>*	--	.17*			.17	.20	1,101.9
Group 2 (Neg.)	<u>.14</u>*	-.11*	--	-.15*			.15	.27	980.4
Group 3 (Neg.)	<u>.45*</u>	.24*	<u>-.23</u>*	-.19*			.12	.26	1,279.6
Group 4 (Neg.)	.17*	--	--	-.16*			.13	.23	625.8
				Georgia Tech					
Group 1 (Pos.)	.22*	<u>-.71</u>*	--		.20*		.11	.23	1,184.8
Group 2 (Pos.)			--						
Group 3 (Pos.)	.42*	-.38*				.23*	.16	.34	1,497.0
Group 4 (Pos.)	.33*	--	--			.18*	.13	.33	805.3
Group 1 (Neg.)	.12*	<u>-1.01</u>*	--	<u>-.15</u>*			.13	.24	1,326.7
Group 2 (Neg.)	<u>.19</u>*	-.14*	--	-.15*			.11	.32	1,135.5
Group 3 (Neg.)	.40*		<u>-.48</u>*	-.17*			.17	.27	1,646.7
Group 4 (Neg.)	.21*	--	--	-.18*			.14	.31	824.3
				Both					
Group 1 (Pos.)	.22*	<u>-.64</u>*	--		<u>.20</u>*		.11	.23	2,234.5
Group 2 (Pos.)	<u>.25</u>*	<u>.05</u>*	--		.18*		.08	.30	1,681.1
Group 3 (Pos.)	.47*	.13*	-.28*	.10*		<u>.18*</u>	.16	.36	2,781.0
Group 4 (Pos.)	.34*	--	--		.14*		.13	.34	1,494.3
Group 1 (Neg.)	.09*	<u>-.91</u>*	--	-.13*		<u>.09</u>	.15	.24	2,489.1
Group 2 (Neg.)	<u>.17</u>*	-.13*	--	-.13*		.14*	.13	.30	2,128.1
Group 3 (Neg.)	.47*	.20*	<u>-.32</u>*	-.17*		.14*	.17	.28	2,969.2
Group 4 (Neg.)	.19*	--	--	-.16*		.13*	.14	.27	1,458.3

Note. R = dummy codes for ratings, R1: (Group 1 = Rating 1, Group 2 = Rating 4, Group 3 = Rating 7, Group 4 = Rating 11), R2: (Group 1 = Rating 3, Group 2 = Rating 6, Group 3 = Rating 8), R3: (Group 3 = Rating 10), Inter. = Interaction. Slopes of parameters allowed to vary across ratings are underlined.
**p* < .05.

Table 24. Multilevel Modeling Analyses with Level 1 and Level 2 Predictors (BIS+/BAS+)

Rating Group	R_1	R_2	R_3	BIS+	BAS+	Inter.	σ^2	τ_{00}	-2LL
				ASU					
Group 1 (Pos.)	.22*	<u>-.55</u>*	--		<u>.48</u>*		.11	.24	1,024.7
Group 2 (Pos.)	.26*	.07*	--		.46*		.09	.32	744.6
Group 3 (Pos.)	<u>.47</u>*	.14*	<u>-.24</u>*		.43*		.11	.40	1,259.3
Group 4 (Pos.)	.34*	--	--		.32*		.13	.34	680.7
Group 1 (Neg.)		<u>-.82</u>*	--	-.14*			.17	.21	1,108.5
Group 2 (Neg.)	<u>.14</u>*	-.11*	--	-.14*			.15	.27	982.5
Group 3 (Neg.)	<u>.45</u>*	.24*	<u>-.23</u>*	-.19*			.12	.27	1,282.4
Group 4 (Neg.)	.17*	--	--	.17*			.13	.23	627.6
				Georgia Tech					
Group 1 (Pos.)	.22*	<u>-.71</u>*	--		.36*	.21*	.11	.20	1,167.1
Group 2 (Pos.)	<u>.23</u>*		--		<u>.21</u>*	.21*	.09	.23	901.9
Group 3 (Pos.)	.42*	-.38*				.37*	.16	.33	1,492.3
Group 4 (Pos.)	.33*	--	--		.26*	.28*	.13	.31	795.7
Group 1 (Neg.)	.12*	<u>-1.01</u>*	--	-.18*			.13	.27	1,317.8
Group 2 (Neg.)	<u>.19</u>*	-.14*	--	-.19*			.11	.31	1,129.0
Group 3 (Neg.)	.40*		<u>-.48</u>*	-.19*			.17	.27	1,643.9
Group 4 (Neg.)	.21*	--	--	-.22*			.14	.30	818.7
				Both					
Group 1 (Pos.)	.22*	<u>-.64</u>*	--		<u>.42</u>*		.11	.22	2,201.8
Group 2 (Pos.)	<u>.25</u>*	.05*	--		.35*		.08	.28	1,665.4
Group 3 (Pos.)	.47*	.13*	-.28*		.31*	<u>.23</u>*	.16	.34	2,769.2
Group 4 (Pos.)	.34*	--	--	<u>-.08</u>	.33*		.13	.29	1,473.3
Group 1 (Neg.)	.09*	<u>-.91</u>*	--	-.16*			.15	.26	2,479.1
Group 2 (Neg.)	<u>.17</u>*	-.13*	--	<u>-.17</u>*			.13	.26	2,119.5
Group 3 (Neg.)	.47*	.20*	<u>-.32</u>*	-.18*			.17	.28	2,968.4
Group 4 (Neg.)	.19*	--	--	-.19*			.14	.27	1,458.0

Note. R = dummy codes for ratings, R1: (Group 1 = Rating 1, Group 2 = Rating 4, Group 3 = Rating 7, Group 4 = Rating 11), R2: (Group 1 = Rating 3, Group 2 = Rating 6, Group 3 = Rating 8), R3: (Group 3 = Rating 10), Inter. = Interaction. Slopes of parameters allowed to vary across ratings are underlined.
**p* < .05.

Table 25. Multilevel Modeling Analyses with Level 1 and Level 2 Predictors (Punishment Expectancy/Reward Expectancy)

Rating Group	R_1	R_2	R_3	PE	RE	Inter.	σ^2	τ_{00}	-2LL
					ASU				
Group 1 (Pos.)	.22*	-.56*	--		.37*		.11	.26	1,006.9
Group 2 (Pos.)	.25*	.07*	--		.34*		.09	.31	731.6
Group 3 (Pos.)	.46*	.13*	-.24*		.31*		.11	.40	1,245.2
Group 4 (Pos.)	.34*	--	--		.38*		.13	.30	657.2
Group 1 (Neg.)		-.81*	--	-.08		.16	.15	.20	1,072.0
Group 2 (Neg.)	.14*	-.12*	--	-.06	.13*		.13	.28	956.1
Group 3 (Neg.)	.44*	.23*	-.22*		.12*		.12	.27	1,265.7
Group 4 (Neg.)	.17*	--	--		.05	.10	.14	.23	623.0
					Georgia Tech				
Group 1 (Pos.)	.22*	-.71*	--		.22*		.11	.21	1,173.1
Group 2 (Pos.)	.23*		--		.17*		.09	.25	910.8
Group 3 (Pos.)									
Group 4 (Pos.)	.33*	--	--		.23*		.13	.31	795.9
Group 1 (Neg.)	.12*	-1.01*	--		.21*		.13	.27	1,328.3
Group 2 (Neg.)	.19*	-.14*	--		.19*		.11	.32	1,134.7
Group 3 (Neg.)	.40*		-.48*		.17*		.17	.28	1,651.8
Group 4 (Neg.)	.21*	--	--		.20*		.14	.27	818.3
					Both				
Group 1 (Pos.)	.22*	-.64*	--		.28*		.11	.22	2,182.4
Group 2 (Pos.)	.25*	.05*	--		.24*		.08	.28	1,650.3
Group 3 (Pos.)	.47*	.13*	-.28*		.20*		.16	.37	2,767.1
Group 4 (Pos.)	.34*	--	--		.30*		.13	.31	1,456.2
Group 1 (Neg.)	.10*	-.90*	--		.17*		.14	.25	2,435.2
Group 2 (Neg.)	.17*	-.13*	--		.16*		.12	.29	2,095.2
Group 3 (Neg.)	.47*	.20*	-.31*		.13*		.17	.27	2,946.5
Group 4 (Neg.)	.19*	--	--		.15*		.14	.26	1,456.7

Note. R = dummy codes for ratings, R1: (Group 1 = Rating 1, Group 2 = Rating 4, Group 3 = Rating 7, Group 4 = Rating 11), R2: (Group 1 = Rating 3, Group 2 = Rating 6, Group 3 = Rating 8), R3: (Group 3 = Rating 10), Inter. = Interaction. Slopes of parameters allowed to vary across ratings are underlined.
*$p < .05$.

Table 26. Multilevel Modeling Analyses with Level 1 and Level 2 Predictors (Neuroticism/Extraversion)

Rating Group	R_1	R_2	R_3	N	E	Inter.	σ^2	τ_{00}	-2LL
				ASU					
Group 1 (Pos.)	.22*	$\underline{-.56}$*	--		.21*		.11	.29	1,026.7
Group 2 (Pos.)	.25*	.07*	--		.21*	-.19*	.09	.33	742.0
Group 3 (Pos.)	$\underline{.46}$*	.13*	$\underline{-.24}$*		.17*		.11	.42	1,255.6
Group 4 (Pos.)	.35*	--	--	$\underline{-.14}$	.17*		.13	.22	664.4
Group 1 (Neg.)		$\underline{-.81}$*	--	-.11			.15	.22	1,082.4
Group 2 (Neg.)	$\underline{.14}$*	-.12*	--	-.12			.13	.28	958.1
Group 3 (Neg.)	$\underline{.44}$*	.23*	$\underline{-.22}$*	-.16*			.12	.27	1,263.3
Group 4 (Neg.)	.17*	--	--	-.15*			.14	.23	628.4
				Georgia Tech					
Group 1 (Pos.)	.22*	$\underline{-.71}$*	--		.12*		.11	.22	1,184.8
Group 2 (Pos.)	$\underline{.23}$*		--	-.12*	$\underline{.05}$		.09	.20	905.3
Group 3 (Pos.)	.42*	-.38*			.16*		.16	.33	1,495.2
Group 4 (Pos.)	.33*	--	--		.14*		.13	.33	803.0
Group 1 (Neg.)	.12*	$\underline{-1.01}$*	--	$\underline{-.18}$*			.13	.24	1,311.5
Group 2 (Neg.)	$\underline{.19}$*	-.14*	--	$\underline{-.21}$*			.11	.24	1,116.9
Group 3 (Neg.)	.40*		$\underline{-.48}$*	-.20*			.17	.26	1,643.0
Group 4 (Neg.)	.21*	--	--	$\underline{-.26}$*	$\underline{-.12}$*		.14	.17	788.4
				Both					
Group 1 (Pos.)	.22*	$\underline{-.64}$*	--		.15*		.11	.21	2,213.5
Group 2 (Pos.)	$\underline{.25}$*	.05*	--		$\underline{.14}$*		.08	.25	1,660.9
Group 3 (Pos.)	.47*	.13*	-.28*		.16*		.16	.37	2,770.4
Group 4 (Pos.)	.34*	--	--		.16*		.13	.33	1,482.5
Group 1 (Neg.)	.10*	$\underline{-.90}$*	--	$\underline{-.16}$*			.14	.24	2,434.1
Group 2 (Neg.)	$\underline{.17}$*	-.13*	--	$\underline{-.18}$*			.12	.24	2,085.1
Group 3 (Neg.)	.47*	.20*	$\underline{-.32}$*	-.22*	-.07*		.17	.28	2,941.5
Group 4 (Neg.)	.19*	--	--	$\underline{-.20}$*			.14	.23	1,445.6

Note. R = dummy codes for ratings, R1: (Group 1 = Rating 1, Group 2 = Rating 4, Group 3 = Rating 7, Group 4 = Rating 11), R2: (Group 1 = Rating 3, Group 2 = Rating 6, Group 3 = Rating 8), R3: (Group 3 = Rating 10), Inter. = Interaction. Slopes of parameters allowed to vary across ratings are underlined.
**p* < .05.

Level 2 variance present in the models ($\bar{\tau}_{00}$ with Level 1 predictors = .30, $\bar{\tau}_{00}$ with Level 1 and Level 2 predictors = .27, $\Delta\bar{\tau}_{00}$ = .03).

The results support Hypotheses 6a and 6b as adding Level 2 predictors significantly improved model fit in virtually every model (97 percent for ASU and 94 percent for Georgia Tech), and the models with improved fit tended to include a significant Level 2 fixed effect (87 percent for ASU and 100 percent for Georgia Tech). In addition, the amount of Level 2 variance decreased with the addition of the Level 2 predictors (ASU: $\Delta\bar{\tau}_{00}$ = .02, Georgia Tech: $\Delta\bar{\tau}_{00}$ = .03). The results indicate that negatively- and positively-toned characteristics continue to influence participants' ratings of course descriptions in models that also include the task condition in the model.

Cross-level interactions added. It was predicted in Hypotheses 6c and 6d that the cross-level interaction between the positively- and negatively-toned characteristics and the task conditions would be significant predictors in models that also included the task conditions. Table 27 through Table 30 display the multilevel models with the cross-level interaction terms added and tested. The results for a model with a cross-level interaction were only reported if the fit of the model improved beyond the models with Level 1 and Level 2 predictors. Although the fifth and sixth interaction terms were possible for the third rating group, as the fifth and sixth interaction terms were not significant in any models they were not included in Table 27 through Table 30. It was predicted in the sixth hypothesis that the addition of the cross-level interactions would also improve the fit of 50 percent or more of the models, and of those models, 50 percent or more would include a significant cross-level interaction fixed effect. In addition, the amount of Level 1 variance should decrease by σ^2 = .02 or greater and the amount of Level 2

Table 27. Multilevel Modeling Analyses with Level 1 Predictors, Level 2 Predictors, and Cross-Level Interaction Terms (BIS/BAS)

Group	R_1	R_2	R_3	BIS	BAS	Inter.	I_1	I_2	I_3	I_4	σ^2	τ_{00}	-2LL
ASU: Positively-Toned Ratings													
Group 1			--										
Group 2			--										
Group 3													
Group 4	.34*	--	--	.03			<u>.14</u>*		--	--	.09	.38	675.2
ASU: Negatively-Toned Ratings													
Group 1			--										
Group 2	<u>.14</u>*	-.12*	--	-.15*	.03				<u>.00</u>	-.16*	.12	.27	961.6
Group 3													
Group 4		--	--						--	--			
Georgia Tech: Positively-Toned Ratings													
Group 1	.21*	<u>-.71</u>*	--	.01	.20*			<u>-.06</u>	-.15*		.09	.23	1,162.1
Group 2			--										
Group 3	.42*	-.38*			.05	.24*		<u>.03</u>			.15	.34	1,487.2
Group 4	.33*	--	--		.16	.19*		-.14*	--	--	.12	.32	797.9
Georgia Tech: Negatively-Toned Ratings													
Group 1	.12*	<u>-1.01</u>*	--	<u>-.14</u>*	.04			<u>-.06</u>			.13	.21	1,319.4
Group 2			--										
Group 3													
Group 4		--	--						--	--			
Both: Positively-Toned Ratings													
Group 1	.22*	<u>-.64</u>*	--	.04	<u>.20</u>*		<u>.01</u>		-.13*		.09	.24	2,212.3
Group 2	<u>.25</u>*	.06*	--		.18*					<u>.07</u>	.08	.30	1,673.9
Group 3	.48*	.13*	-.28*	.10*		<u>.07</u>*	<u>.06</u>				.15	.36	2,767.1
Group 4	.34*	--	--	-.01	.14*		.08*		--	--	.13	.34	1,487.0
Both: Negatively-Toned Ratings													
Group 1			--										
Group 2	<u>.17</u>*	-.13*	--	-.13*	-.02	.13*			<u>-.03</u>	-.09*	.11	.30	2,111.7
Group 3	.47*	.20*	<u>-.32</u>*	-.16*			<u>.05</u>				.16	.28	2,958.3
Group 4		--	--						--	--			

Note. R = dummy codes for ratings, R1: (Group 1 = Rating 1, Group 2 = Rating 4, Group 3 = Rating 7, Group 4 = Rating 11), R2:(Group 1 = Rating 3, Group 2 = Rating 6, Group 3 = Rating 8), R3: (Group 3 = Rating 10), Inter. = Interaction, I = cross level interactions, I_1: (Group 1 = BIS/Rating 1, Group 2 = BIS/Rating 4, Group 3 = BIS/Rating 7, Group 4 = BIS/Rating 11), I_2: (Group 1 = BAS/Rating 1, Group 2 = BAS/Rating 4, Group 3 = BAS/Rating 7, Group 4 = BAS/Rating 11), I_3: (Group 1 = BIS/Rating 3, Group 2 = BIS/Rating 6, Group 3 = BIS/Rating 8), I_4: (Group 1 = BAS/Rating 3, Group 2 = BAS/Rating 6, Group 3 = BAS/Rating 8), I_5: (Group 3 = BIS/Rating 10), I_6: (Group 3 = BAS/Rating 10). Slopes of parameters allowed to vary across ratings are underlined.
*$p < .05$.

Table 28. Multilevel Modeling Analyses with Level 1 Predictors, Level 2 Predictors, and Cross-Level Interaction Terms (BIS+/BAS+)

Group	R_1	R_2	R_3	BIS+	BAS+	Inter.	I_1	I_2	I_3	I_4	σ^2	τ_{00}	-2LL
ASU: Positively-Toned Ratings													
Group 1			--										
Group 2			--										
Group 3													
Group 4	.35*	--	--		.30*		.13*	<u>.12</u>	--	--	.12	.34	662.8
ASU: Negatively-Toned Ratings													
Group 1			--										
Group 2	<u>.14</u>*	-.11*	--	-.14*					<u>-.02</u>	-.23*	.08	.23	964.4
Group 3													
Group 4		--	--						--	--			
Georgia Tech: Positively-Toned Ratings													
Group 1			--										
Group 2			--										
Group 3	.42*	-.38*		.02		.35*	<u>.06</u>				.15	.33	1,483.0
Group 4	.32	--	--		.27*	.28*		<u>-.16</u>	--	--	.10	.33	779.5
Georgia Tech: Negatively-Toned Ratings													
Group 1			--										
Group 2			--										
Group 3													
Group 4		--	--						--	--			
Both: Positively-Toned Ratings													
Group 1	.22*	<u>-.64</u>*	--	-.03	<u>.42</u>*			<u>.09</u>	-.13*		.10	.22	2,180.3
Group 2			--										
Group 3	.47*	.13*	-.28*	.04	.29*	<u>.29</u>*	<u>.04</u>	.11			.15	.34	2,748.7
Group 4	.34*	--	--	<u>-.08</u>	<u>.33</u>*		.09*		--	--	.13	.29	1,465.7
Both: Negatively-Toned Ratings													
Group 1			--										
Group 2	<u>.17</u>*	-.13*	--	<u>-.17</u>*			-.15*			-.13*	.13	.26	2,111.8
Group 3													
Group 4		--	--						--	--			

Note. R = dummy codes for ratings, R1: (Group 1 = Rating 1, Group 2 = Rating 4, Group 3 = Rating 7, Group 4 = Rating 11), R2:(Group 1 = Rating 3, Group 2 = Rating 6, Group 3 = Rating 8), R3: (Group 3 = Rating 10), Inter. = Interaction, I = cross level interactions, I_1: (Group 1 = BIS+/Rating 1, Group 2 = BIS+/Rating 4, Group 3 = BIS+/Rating 7, Group 4 = BIS+/Rating 11), I_2: (Group 1 = BAS+/Rating 1, Group 2 = BAS+/Rating 4, Group 3 = BAS+/Rating 7, Group 4 = BAS+/Rating 11), I_3: (Group 1 = BIS+/Rating 3, Group 2 = BIS+/Rating 6, Group 3 = BIS+/Rating 8), I_4: (Group 1 = BAS+/Rating 3, Group 2 = BAS+/Rating 6, Group 3 = BAS+/Rating 8), I_5: (Group 3 = BIS+/Rating 10), I_6: (Group 3 = BAS+/Rating 10). Slopes of parameters allowed to vary across ratings are underlined.
*$p < .05$.

Table 29. Multilevel Modeling Analyses with Level 1 Predictors, Level 2 Predictors, and Cross-Level Interaction Terms (Punishment Expectancy/Reward Expectancy)

Group	R_1	R_2	R_3	PE	RE	Inter.	I_1	I_2	I_3	I_4	σ^2	τ_{00}	-2LL
ASU: Positively-Toned Ratings													
Group 1	.20*	-.56*	--	-.08	.36*		-.09				.08	.26	991.8
Group 2			--										
Group 3													
Group 4	.34*	--	--		.38*		.13*		--	--	.13	.30	652.8
ASU: Negatively-Toned Ratings													
Group 1			--										
Group 2	.13*	-.11*	--	-.07	.13*				-.04		.09	.29	938.2
Group 3	.44*	.23*	-.22*		.12*		-.14*	.09			.12	.27	1,253.9
Group 4		--	--						--	--			
Georgia Tech: Positively-Toned Ratings													
Group 1	.22*	-.71*	--	.04	.23*		-.06				.08	.22	1,149.8
Group 2			--										
Group 3	.41*	-.38*		-.06			.03				.14	.35	1,485.1
Group 4		--	--						--	--			
Georgia Tech: Negatively-Toned Ratings													
Group 1	.12*	-1.01*	--		.21*			-.15*			.12	.28	1,318.5
Group 2			--										
Group 3													
Group 4	.21*	--	--		.20*			-.11*	--	--	.14	.27	813.7
Both: Positively-Toned Ratings													
Group 1	.21*	-.64*	--	-.01	.28*		-.07			.00	.08	.23	2,146.6
Group 2			--										
Group 3	.47*	.13*	-.28*	-.02	.20*			-.03			.15	.37	2,742.9
Group 4	.34*	--	--	-.04	.29*		.06		--	--	.12	.31	1,449.5
Both: Negatively-Toned Ratings													
Group 1	.10*	-.90*	--		.16*			-.07			.12	.25	2,422.7
Group 2	.16*	-.13*	--	-.10	.14*		-.02				.12	.28	2,083.2
Group 3													
Group 4	.19	--	--		.16*			-.08*	--	--	.14	.26	1,452.4

Note. R = dummy codes for ratings, R1: (Group 1 = Rating 1, Group 2 = Rating 4, Group 3 = Rating 7, Group 4 = Rating 11), R2:(Group 1 = Rating 3, Group 2 = Rating 6, Group 3 = Rating 8), R3: (Group 3 = Rating 10), Inter. = Interaction, I = cross level interactions, I_1: (Group 1 = Punishment Expectancy/Rating 1, Group 2 = Punishment Expectancy/Rating 4, Group 3 = Punishment Expectancy/Rating 7, Group 4 = Punishment Expectancy/Rating 11), I_2: (Group 1 = Reward Expectancy/Rating 1, Group 2 = Reward Expectancy/Rating 4, Group 3 = Reward Expectancy/Rating 7, Group 4 = Reward Expectancy/Rating 11), I_3: (Group 1 = Punishment Expectancy/Rating 3, Group 2 = Punishment Expectancy/Rating 6, Group 3 = Punishment Expectancy/Rating 8), I_4: (Group 1 = Reward Expectancy/Rating 3, Group 2 = Reward Expectancy/Rating 6, Group 3 = Reward Expectancy/Rating 8), I_5: (Group 3 = Punishment Expectancy/Rating 10), I_6: (Group 3 = Reward Expectancy/Rating 10). Slopes of parameters allowed to vary across ratings are underlined.
*p < .05.

Table 30. Multilevel Modeling Analyses with Level 1 Predictors, Level 2 Predictors, and Cross-Level Interaction Terms (Neuroticism/Extraversion)

Group	R_1	R_2	R_3	N	E	Inter.	I_1	I_2	I_3	I_4	σ^2	τ_{00}	-2LL
ASU: Positively-Toned Ratings													
Group 1	.21*	-.56*	--	.01	.22*		-.01				.09	.29	1,019.7
Group 2			--										
Group 3													
Group 4	.35*	--	--	-.14	.17*		.13*		--	--	.13	.22	659.5
ASU: Negatively-Toned Ratings													
Group 1		-.80*	--	-.09	.05		.04	.06			.11	.23	1,066.0
Group 2	.13*	-.12*	--	-.12			-.04				.13	.28	951.0
Group 3	.44*	.24*	-.22*	-.16*					-.07		.11	.27	1,255.6
Group 4	.17*	--	--	-.15*			.01		--	--	.10	.25	617.9
Georgia Tech: Positively-Toned Ratings													
Group 1	.22*	-.70*	--	-.04	.10*		-.02		-.13*		.08	.23	1,149.3
Group 2	.25*	.04	--	-.11*	.04					.10*	.08	.21	893.3
Group 3	.42*	-.38*		.09	.15*		.03				.14	.34	1,481.4
Group 4	.33*	--	--		.14*			.33*	--	--	.12	.33	799.0
Georgia Tech: Negatively-Toned Ratings													
Group 1			--										
Group 2			--										
Group 3													
Group 4	.21*	--	--	-.26*	-.12*		-.16*		--	--	.13	.17	776.0
Both: Positively-Toned Ratings													
Group 1	.21*	-.64*	--	-.02	.15*		-.01				.08	.22	2,187.2
Group 2	.25*	.05*	--		.14*					.09*	.08	.25	1,647.4
Group 3	.47*	.13*	-.28*	.03	.17*		.05	.07*			.15	.37	2,752.9
Group 4	.34*	--	--	-.08	.13*		.09*		--	--	.13	.33	1,473.1
Both: Negatively-Toned Ratings													
Group 1	.10*	-.90*	--	-.15*			.03				.12	.25	2,422.1
Group 2	.17*	-.13*	--	-.21*	-.07*					.02	.10	.23	2,067.3
Group 3	.46*	.20*	-.32*	-.22*	-.08*		.02				.16	.28	2,931.9
Group 4	.19*	--	--	-.22*	-.07*			-.12*	--	--	.14	.23	1,430.2

Note. R = dummy codes for ratings, R1: (Group 1 = Rating 1, Group 2 = Rating 4, Group 3 = Rating 7, Group 4 = Rating 11), R2:(Group 1 = Rating 3, Group 2 = Rating 6, Group 3 = Rating 8), R3: (Group 3 = Rating 10), Inter. = Interaction, I = cross level interactions, I_1: (Group 1 = Neuroticism/Rating 1, Group 2 = Neuroticism/Rating 4, Group 3 = Neuroticism/Rating 7, Group 4 = Neuroticism/Rating 11), I_2: (Group 1 = Extraversion/Rating 1, Group 2 = Extraversion/Rating 4, Group 3 = Extraversion/Rating 7, Group 4 = Extraversion/Rating 11), I_3: (Group 1 = Neuroticism/Rating 3, Group 2 = Neuroticism/Rating 6, Group 3 = Neuroticism/Rating 8), I_4: (Group 1 = Extraversion/Rating 3, Group 2 = Extraversion/Rating 6, Group 3 = Extraversion/Rating 8), I_5: (Group 3 = Neuroticism/Rating 10), I_6: (Group 3 = Extraversion/Rating 10). Slopes of parameters allowed to vary across ratings are underlined.
$^*p < .05$.

variance should decrease by τ_{00} = .02 or greater.

For the ASU sample, adding the cross-level interactions significantly improved the fit of 44 percent of the models. Of the 14 models that cross-level interactions significantly improved fit, 50 percent included a cross-level interaction with a significant fixed effect. The inclusion of the cross-level interactions caused a reduction in the amount of Level 1 variance ($\bar{\sigma}^2_{\text{with Level 1 and Level 2 predictors}} = .12$, $\bar{\sigma}^2\ \bar{\tau}_{00\ \text{with cross-level interactions}} = .11$, $\Delta\bar{\sigma}^2 = .01$), but not a decrease in the amount of Level 2 variance ($\bar{\tau}_{00\ \text{with Level 1 and Level 2 predictors}} = .28$, $\bar{\tau}_{00\ \text{with cross-level interactions}} = .28$).

For the Georgia Tech sample, adding cross-level interactions significantly improved the fit of 50 percent of the models. Of the 15 models that cross-level interactions significantly improve fit, 56 percent included a cross-level interaction with a significant fixed effect. The inclusion of the cross-level interactions also caused a reduction in the amount of Level 1 variance ($\bar{\sigma}^2_{\text{with Level 1 and Level 2 predictors}} = .13$, $\bar{\sigma}^2\ \bar{\tau}_{00\ \text{with cross-level interactions}} = .12$, $\Delta\bar{\sigma}^2 = .01$), but no decrease in the amount of Level 2 variance ($\bar{\tau}_{00\ \text{with Level 1 and Level 2 predictors}} = .25$, $\bar{\tau}_{00\ \text{with cross-level interactions}} = .28$). As the variance components are estimated, a slight increase in variance with the addition of predictors does not indicate an error in the procedures used to compute the analysis.

Improvement in model fit from the addition of cross-level interactions was inconsistent. A significant improvement in model fit was achieved in 50 percent or more of the models from the Georgia Tech sample only. Of those models with a significant improvement in model fit from both samples, 50 percent or more included a cross-level interaction term that was a significant fixed effect. Although a slight decrease was observed in Level 1 variance, the amount of Level 2 variance did not decrease. As stated earlier, the focus of the multilevel modeling analyses was on explaining Level 2 variance—the explanation of individual differences as opposed to intra-individual differences. Therefore, the lack of reduction in Level 2 variance indicates that the addition of the cross-level interactions did not contribute to the prediction of individual differences, and instead contributed to the prediction of intra-individual differences. In summary, the results do not support Hypotheses 6c or 6d.

Results Summary

The purpose of this section is to provide a brief summary of the results with a focus on each hypothesis. Only results from the negatively- and positively-toned characteristics that were examined throughout the results section from the main study (i.e., BIS/BAS, BIS+/BAS+, Reward Sensitivity/Punishment Sensitivity, and Neuroticism/Extraversion) are reported in this section. Other than the results for Punishment Sensitivity, analyses of the psychometric properties of the predictors and criteria did not present any areas of concern. The reliability analysis indicated that removing items from the Punishment Expectancy would not have improved the internal consistency of the scale.

The predictions expressed in the first two hypotheses were used to examine the convergent validity of the predictors used in the study. The convergent validities among the scales derived from the Reward Sensitivity Theory were examined in Hypothesis 1 and the convergent validity between the scales derived from the Reward Sensitivity Theory and the corresponding scales from the IPIP representing the Big Five was examined in Hypothesis 2. The intercorrelation among the negatively-toned characteristics (BIS, BIS+, Punishment Sensitivity, and Neuroticism) either met (*r* between .40 and .60) or exceeded expectations. BAS+ fell within the expected range (*r* between .40 and .60) for all comparisons predicted in hypotheses 1 and 2. BAS failed to correlate within the expected range with Reward Expectancy (r = .39) with the ASU sample and Reward Expectancy (r = .36) and Extraversion (r = .33) with the Georgia Tech sample. Reward Expectancy failed to correlate with BAS in the ASU and Georgia Tech sample, as just described. In general, the results do not suggest any areas of concern that would adversely affect the interpretation of later analyses using the predictor scales and are consistent with past research findings (e.g., Torrubia et al., 2001).

The criteria for the study were made up of a composite of either negatively- or positively-toned items from three or four course descriptions. The average internal consistency reliability estimates were excellent ($\overline{\alpha}_{ASU}$ = .91, $\overline{\alpha}_{Georgia\,Tech}$ = .90). The third hypothesis represented a manipulation check designed to determine whether participants rated course descriptions differently based on the task condition (i.e., pattern of valences of the comments included in the course description). Polynomial contrasts were computed by each rating group to determine whether there was a significant linear or quadratic trend. In support of Hypothesis 3, a linear trend was significant in all of the models from both samples and the effect sizes met predictions (η^2 = .10 or higher). In addition, a significant quadratic trend was found in 67 percent of the models from both samples, most of which met or exceeded the predicted effect size (75 percent for the ASU sample, 100 percent for the Georgia Tech sample). Two additional analyses were conducted to determine the effect of varying the course content had on participants' ratings. The results suggest that varying the comment valence pattern produced a stronger effect in terms of causing differences in participants' ratings than varying the course content.

The predictions stated in Hypothesis 4 examined the validity of the negatively- and positively-toned characteristics for predicting the course description ratings. In general and across ratings, support for Hypothesis 4 was not entirely consistent across both samples. However, a host of comment valence patterns were included in the study to provide a wide variety of task conditions for investigation, and support for Hypothesis 4 was less mixed when just the ratings most likely to support the hypothesis based on past research and the Reward Sensitivity Theory (Gray, 1987, 1994; Gray et al., 1983; Pickering et al., 1995; Pickering & Gray, 1999) were examined. That is, when examining the predictions made in Hypothesis 4 with just the ratings most likely to support expectations the results remained somewhat inconsistent for the negatively-toned characteristics with just one of the predictors generalizing across both samples, but provided more consistent support for predictions with the positively-toned characteristics.

In the fifth hypothesis, I proposed that the interaction between the negatively- and positively-toned characteristics would significantly predict course ratings. Across both samples, the interaction effect was significant in twelve percent of the models. The results support the presences of an interaction effect and the need to examine whether an interaction effect is present. However, the nature of the interaction (see Appendix A) was inconsistent across predictor pairs and samples.

Multilevel modeling analysis was used to examine whether the negatively- and positively-toned characteristics would remain significant predictors in models that also included the task condition. The findings provide support for Hypotheses 6a and 6b and were based on the number of models with significant improvement in fit after adding Level 2 predictors among other criteria. Hypotheses 6c and 6d stated that the cross-level interactions of the negatively- and positively-toned characteristics with task condition would significantly predict ratings in models that also included the task condition in the model. Hypotheses 6c and 6d were not supported.

CHAPTER 8

MAIN STUDY: DISCUSSION

The organization of the discussion section mirrors the layout of the Results section. First, the implications of analyses focusing on the predictors followed by the criteria are discussed. The results from the analyses of the predictors and criteria support the validity of the later findings. Next, the implications of the correlational results are considered. The analyses of the predictive efficiency of the personality system derived from the Reward Sensitivity Theory are the most central to the primary objective of the study and are the most similar to analyses conducted in past research (e.g., A. Gomez & Gomez, 2002; R. Gomez, Cooper, McOrmond, & Tatlow, 2004). The implications of supporting the separable subsystems hypothesis rather than the joint subsystems hypothesis are discussed next, which utilizes an interpretation of the results from the tests for interaction effects. Finally, the results from the multilevel modeling analyses are discussed.

Predictors

Two strategies were used in an attempt to increase the internal consistency reliability estimates of the measures initially administered in the pilot study and used again in the main study. The results suggest that including additional items increased the internal consistency reliability estimates of the revised BIS/BAS Scales over the original BIS/BAS Scales. Based on Cicchetti's (1994) guidelines, the internal consistency for the original BIS/BAS Scales varied from the unacceptable to the good range (pilot study: α varies from .66 to .78, ASU: α varies from .64 to .81, Georgia Tech: α varies from .62

to .82) and the revised BIS/BAS Scales varied from the fair to the excellent range (ASU: α varies from .81 to .90, Georgia Tech: α varies from .79 to .93).

In general, the convergent validity of the BIS and BAS scales was supported. However, consistent with past research (Torrubia et al., 2001), the discriminant validity of the scales assessing BIS and BAS sensitivity was less consistent with expectations derived from the Reward Sensitivity Theory. BIS-Reward Responsiveness and BIS-Reward Responsiveness+ correlated significantly positively with BIS and BIS+ (ASU: r varied from .25 to .41, Georgia Tech: r varied from .28 to .35), which is not consistent with expectations derived from the Reward Sensitivity Theory. Most likely, the BIS/BAS Scales are in need of refinement, particularly BIS-Reward Responsiveness (cf. Torrubia et al., 2001).

Criteria

The predictions stated in the third hypothesis were examined using polynomial contrasts to determine whether participants rated course descriptions with less aversive comments and more positive comments more highly than course descriptions with more aversive comments and less positive comments. A linear trend was significant in every model, whereas a quadratic trend was not always significant. A linear trend suggests that, on average, the increase in ratings from a positive comment is equal to the decrease in ratings from an aversive comment. As the results suggest that positive comments are associated with an increase in ratings and aversive comments with a decrease in ratings, a quadratic effect would suggest that, on average, the increase in ratings from a positive comment is not equal to the decrease in ratings from an aversive comment, such that either an aversive or positive comment is more powerful than the other.

The results from the Level 1 predictors-only models from the multilevel modeling analyses also provide support for Hypothesis 3. To create the Level 1 predictors, the task conditions (i.e., comment valence patterns) were dummy coded. Every model included at least one significant Level 1 predictor and the addition of the Level 1 predictors resulted in a significant improvement in the fit of every model. The results indicate that the dummy coded task condition variables significantly influenced participants' ratings of the course descriptions. Thus, the results from the Level 1 predictors-only models are consistent with the results from the polynomial contrasts in terms of providing support for the conclusion that participants rate course descriptions differently based on the valence pattern of the comments.

Correlational Results

In general and consistent with Reward Sensitivity Theory (Gray, 1987, 1994; Gray et al., 1983; Pickering et al., 1995; Pickering & Gray, 1999), the correlational results supported the distinction between positively-toned predictors and positively-toned ratings versus negatively-toned predictors and negatively-toned ratings. Across both samples, seven correlations were within the predicted range of effect sizes (between .2 and .4) when correlating the positively-toned characteristics with the negatively-toned ratings ($\bar{r}$ = .01). Conversely, when correlating the negatively-toned characteristics with the positively-toned ratings, two correlations were within the predicted range of effect sizes (between .2 and .4; $\bar{r}$ = -.02). However, 75 correlations were within the predicted range of effect sizes when correlating the positively-toned characteristics with the positively-toned ratings ($\bar{r}$ = .14), and 36 correlations were within the predicted range of effect sizes when correlating the negatively-toned characteristics with the negatively-toned ratings ($\bar{r}$ = -.16).

When the emotional tone of the predictors and ratings were aligned, the predictors tended to predict a series of ratings without regard for any of the combinations of aversively-, positively-, or neutrally-toned comments included in the course description. The average correlation was computed for all of the negatively- and positively-toned characteristics for each sample for the hypothesized ratings and for all of the ratings (see Table 21). A significance test of the difference between two correlations revealed no significant differences between the correlations with the hypothesized ratings and the correlations with all of the ratings (ASU negatively-toned characteristics: $r_{\text{hypothesized ratings}} = -.14$, $r_{\textit{all ratings}} = -.14$; Georgia Tech negatively-toned characteristics: $r_{\text{hypothesized ratings}} = -.19$, $r_{\textit{all ratings}} = -.18$; ASU positively-toned characteristics: $r_{\text{hypothesized ratings}} = .19$, $r_{\textit{all ratings}} = .17$; Georgia Tech negatively-toned characteristics: $r_{\text{hypothesized ratings}} = .11$, $r_{\textit{all ratings}} = .11$). An additional set of analyses also revealed that there was not a significant difference between the seven hypothesized ratings versus the five non-hypothesized ratings for either valence. The results of these analyses suggest that the influence of the negatively- and positively-toned characteristics is more general than hypothesized.

In general, the results based on the average correlations were not entirely consistent for the fourth hypothesis. The inconsistency came from a lack of generalizability from one sample to the other sample. In addition, many correlations were significant and in the direction hypothesized, but the effect size did not fall within the hypothesized range (*r* between .2 and .4). Greater consistency was found when examining the ratings most likely to yield a result consistent with the predictions made in

Hypothesis 4. Results obtained with the positively-toned characteristics generalized across both samples and supported the fourth hypothesis. However, the results for only one of the four predictors generalized across both samples for the negatively-toned characteristics.

Interactions

By presenting the joint subsystems hypothesis, Corr (2001) heralded the need for researchers invoking the Reward Sensitivity Theory to consider and look for the presence of interactions between the behavioral inhibition system and the behavioral activation system. The presence of significant interaction terms supported both Hypothesis 5 and Corr's call to look for interaction effects. Consistent with past research (Corr, 2002; Jackson & Francis, 2004; Kambouropoulos & Staiger, 2004; see also Zinbarg and Revelle, 1989), however, the form of the interactions was inconsistent and often did not meet expectations based on the joint subsystems hypothesis.

Although the need to investigate potential interaction effects was supported, the results supported expectations derived from the separable subsystems hypothesis to a greater extent than those derived from the joint subsystems hypothesis. Across predictors and samples, an interaction term was significant in 12 percent of the models. Of those models with a significant interaction term, a direct effect was of an equal or greater effect size in 48 percent of the models. On the other hand, a direct effect was significant in 71 percent of the models across predictors and both samples. Of those models with a significant direct effect, an interaction effect was of an equal or greater effect size in only three percent of the models. On average and in support of the separable subsystems hypothesis, the direct effects appeared to be more important in the prediction of the course ratings than the interaction effects.

Although the findings support the separable subsystem hypothesis more than the joint subsystem hypothesis, this may have more to do with the design of the study, particularity the dependent variable, than the strength of the theory behind either hypothesis. That is, the design of this study favored the separable subsystems hypothesis when the ratings were separated into negatively- and positively-toned rating scales. Instead of having a dependent variable with both negatively- and positively-toned variance, the separation of the dependent variable into two scales created a negatively-toned rating scale that was associated with negatively-toned person characteristics and a positively-toned rating scale that was associated with positively-toned person characteristics. As a result, the interaction term significantly predicted the ratings scales in only twelve percent of the models.

Additional research is needed to determine why the form of the interaction effect tends to diverge from predictions made based on the joint subsystems hypothesis (cf. Corr, 2002; Jackson & Francis, 2004; Kambouropoulos & Staiger, 2004; see also Zinbarg and Revelle, 1989). However, as the study design appears to have favored the separable subsystems hypothesis, the study may have provided a less than ideal design to examine the nature of the interaction effects. In general, more consistent support for the joint subsystems hypothesis should be found before attempting to explicate the nature of the interaction effects.

<u>Multilevel Modeling Analyses</u>

The final set of analyses examined the predictive efficiency of the negatively- and positively-toned characteristics with the task condition also included in the model. The results supported the addition of the negatively- and positively-toned characteristics as predicted in Hypotheses 6a and 6b, but not the addition of the cross-level interactions as predicted in Hypotheses 6c and 6d. In terms of the amount of variance accounted for by the predictors and the decrease in model fit, there appeared to be a series of diminishing returns going from adding the Level 1 predictors to adding the Level 2 predictors to adding the cross-level interactions. In fact, the cross-level interactions did not add much to the models in terms of producing a significant improvement in model fit or reducing the amount of variance in the models. As the predictive efficiency of the Level 1 and Level 2 predictors was high, there was most likely not much predictable variance left over for the cross-level interactions to account for, which may have been further exacerbated by the fact that the cross-level interactions were made up of the Level 1 and Level 2 predictors.

CHAPTER 9

CONCLUSIONS

Course selection decisions represent one of the most important tasks undertaken by undergraduate college students (Ackerman, 1996; Babad, 2001; Kerin et al., 1975). Selecting a course that is too difficult or not intellectually stimulating, a course with a poor instructor, or a course that just does not match one's optimal learning style can have adverse consequences on students' interest in the material, their grades in the course, and subsequent career paths and opportunities. To date, research has focused more on the influence of course attributes, particularly the content area of the course, and the self-concept of the students selecting courses (e.g., Marsh and Yeung, 1997; Eccles & Wigfield, 2002; Meece et al., 1990). Less attention has been given to course features, such as how stimulating a course is, and the influence of person characteristics when selecting courses with different features. This study extends the research literature by examining the impact of person attributes based on the Reward Sensitivity Theory on course selection preferences to investigate the manner in which both person and course attributes influence course preference ratings. The study applies the Reward Sensitivity Theory to a new area of study—course selection preferences, and examines the influence of person and course attributes separately as well as their joint influence.

The findings provide preliminary support for the notion that individual differences in punishment sensitivity and reward sensitivity influence the information that students attend to and how students perceive course features. In general, individual differences in punishment sensitivity were associated with lower ratings of a course, but just on the negatively worded ratings (e.g., “This course would be difficult.”), and individual differences in reward sensitivity were associated with higher ratings of a course, but just on the positively worded ratings (e.g., “This course is interesting.”). The effect of individual differences in punishment and reward sensitivity remained significant in models that also accounted for the influence of the course features, which indicates that both person and course attributes play a role in determining students’ course selection preferences.

Implications

The results from the study suggest that course descriptions represent powerful stimuli (or set of stimuli) that activate both the behavioral inhibition system and the behavioral activation system. When activated, the behavioral inhibition system mediates negatively-toned expression through negatively-toned responses and the behavioral activation system mediates positively-toned expression through positively-toned responses. In general, the behavioral inhibition system does not influence behavior on positively-toned response opportunities and the behavioral activation system does not influence behavior on negatively-toned response opportunities. Response options that are both negatively- and positively-toned may provide for the expression of both systems and a greater likelihood of a joint effect in contrast to response scales that separate negative response options from positive response options, such as was done in this study.

The primary difference between the expectations expressed in the hypotheses and the results obtained was that the influence of punishment and reward sensitivity was found to be more pervasive than predicted as the task condition of the course descriptions did not moderate the observed effects. I hypothesized that punishment sensitivity would significantly predict course ratings when a course description included aversive comments and that reward sensitivity would significantly predict course ratings when a course description included appetitive comments. However, punishment sensitivity also significantly predicted course descriptions without aversive comments and reward sensitivity significantly predicted course descriptions without appetitive comments. Significant correlations were observed even when the course descriptions included six neutrally-valenced comments.

Instead, the boundary condition appears to be that punishment sensitivity is associated with a focus on negative responses and reward sensitivity is associated with a focus on positive responses. In general, punishment sensitivity was a significant predictor of the negatively-toned rating scales and reward sensitivity was a significant predictor of the positively-toned rating scales. Although the hypothesized boundary condition regarding the influence of how the stimuli (i.e., course descriptions) were presented was not supported, another boundary condition was supported concerning how participants responded to the stimuli (i.e., the use of the positively- and negatively-toned ratings).

The correspondence between the emotional tone of the person characteristics and the use of rating scales suggests that to obtain a more comprehensive evaluation of a course, the rating instrument should include rating items that assess both positive and negative course attributes. If the breadth of the Reward Sensitivity Theory and past research is also considered, than the results from this study may be generalized to suggest that students' standings on punishment and reward sensitivity influence their interpretation of information in general. Students with a higher standing on punishment sensitivity tend to perceive stimuli more negatively via aversive reactions and students with a higher standing on reward sensitivity tend to perceive stimuli more positively via appetitive reactions.

In an attempt to address past conflicting research findings when applying Reward Sensitivity Theory, Corr (2001) proposed the joint subsystems hypothesis. The joint subsystems hypothesis indicates a set of conditions under which an interaction effect between the behavioral inhibition system and the behavioral activation system is more likely. The main study included all of Corr's conditions that indicate a greater likelihood of an interaction effect. Namely, the stimuli included mixtures of reward and punishment signals, the stimuli rapidly switched back and forth through conditions that were aversive and appetitive, the stimuli were not strongly aversive or appetitive, and the participants varied in levels of BIS and BAS sensitivity. However, results from the moderated regression analyses supported the presence of significant interaction effects in only twelve percent of the models. Accordingly, the results appear more consistent with the separable subsystems hypothesis than the joint subsystems formulation.

Moreover, the design of the study was most likely more favorable to the separable subsystems hypothesis as the response scale that was used to collect the course description ratings was divided into negatively- and positively-toned rating scales. Therefore, a key determinant of whether a study design favors the separable subsystems hypothesis or the joint subsystems hypothesis appears to be whether the criteria used in the study separate negatively- and positively-toned responses, as in this study, or capture both negatively- and positively-toned responses.

Although past research findings have supported the joint influence of BIS and BAS sensitivity on study outcomes, the nature of the interaction effects observed by researchers has not conformed to predictions made based on Corr's (2001) joint subsystems hypothesis (Corr, 2002; Jackson & Francis, 2004; Kambouropoulos & Staiger, 2004; see also Zinbarg and Revelle, 1989). In an attempt to shed light on the conflicting results between predictions and findings in past research, interaction plots were created of all models with significant interaction terms. The nature of the interactions in the plots was inconsistent across predictor pair and sample. Additional research is needed to determine why the nature of the interaction effects differs from predictions. In particular, researchers may consider examining narrower facets of the behavioral inhibition system and the behavioral activation system to determine whether a broad conceptualization of behavioral inhibition and behavioral activation obscures the influence of specific processes operating within the systems. The mixed results suggest that extant measures of behavioral inhibition and behavioral activation are not effective conceptualizations of the systems to use when examining interactive effects and that additional conceptualizations and other determinants and correlates need to be considered. The mixed results suggest that there are determinants that are not accounted for in the analysis of the study results. Alternatively, the joint subsystems hypothesis may require further refinement.

From a practical perspective, if students are unaware of their sensitivity orientation, then they may make course selection decisions based on biased information processing. A critical question for future research pertains to whether such biases are a reflection of a preference for courses that correspond to student's preferred or even optimal learning style, or whether such biases lead to suboptimal course decision making. For example, do students with a higher standing on punishment sensitivity receive higher grades in courses with less aversive features (e.g., challenging course, domineering instructor) than students with a lower standing on punishment sensitivity, and do students with a higher standing on reward sensitivity receive higher grades in courses with more appetitive features (e.g., exciting course, instructor calls on students) than students with a lower standing on reward sensitivity.

In summary, based on Reward Sensitivity Theory, past research, and the results from the studies reported in this dissertation, the potential applications of Reward Sensitivity Theory appear rather broad. The influence of punishment and reward sensitivity appears to be relevant when two conditions are met. First, the stimuli should have the capacity to elicit an emotional response. The stimuli could be negatively- or positively-valenced and direct the response, or the stimuli could be neutral, yet elicit an emotional response. For example, Rusting (1999) found that participants wrote stories with emotionally-valenced content consistent with the valence of person characteristics based on an emotionally ambiguous, yet neutrally-valenced introductory sentence (e.g., "John is resting his head on his hands."). In addition, the expression of an emotional response should be possible. For example, a strong situation (e.g., a funeral) may constrain the expression of certain emotions or of any emotion. When these two conditions are met, students with a higher standing on punishment sensitivity will tend to perceive stimuli as more negative, which is expressed through negatively-toned responses, and students with a higher standing on reward sensitivity will tend to perceive stimuli as more positive, which is expressed through positively-toned responses. As these two conditions are ubiquitous (i.e., stimuli that elicit an emotional response or at least provide an opportunity to express an emotional response and an emotional response is possible), Reward Sensitivity Theory appears to be widely applicable.

Limitations and Strengths

Several limitations and strengths associated with the design of the study should be noted. First, the second part of the study most likely included too many course descriptions in the course description rating task. Participants were given an opportunity to leave a comment at the end of the second part of the study. Of those responding, many commented that Part 2 of the study was repetitive and/or long. The potential problem is that participants may have been less focused toward the end of Part 2 of the study, which may have affected the course description ratings near the end of the task. However, any problems with responses near the end of Part 2 would have been attenuated as the rating composites consisted of a combination of course description ratings administered at the beginning, middle, and end of the task.

In contrast, the method used to calculate criterion ratings represents a strength of this study. Specifically, the ratings used as criteria were composites computed by averaging three to five items and then averaging three to four course descriptions. This resulted in outcome variables with internal consistency reliability estimates ($\alpha \geq .88$) that fell into either the good or excellent range based on Cicchetti's (1994) guidelines. This most likely resulted in an improvement of the psychometric properties of the criteria in comparison to past studies examining course selection preferences that relied on single item ratings (e.g., Kerin et al., 1975; Roberts, 1981).

Conducting the study over the Internet presented advantages and disadvantages. In general, more students seem to sign-up for a study conducted entirely over the Internet. However, experimenters were not present to guide participants through the study. In addition, the environmental press of a lab session most likely ensures that participants complete the study in a more conscientious manner when compared to a study conducted over the Internet, especially if a participant becomes bored or fatigued while completing the study. Initial, uncleaned datasets revealed that a number of participants completed the study multiple times with initial attempts only covering the first few questions. To ensure the integrity of the data, the dataset was thoroughly examined and cleaned (see the Method section for the main study).

Another strength of this research pertains to the use of two independent samples from two separate schools. First, using two samples allows for an examination of replicatability. To the extent that replicatability was achieved (as both samples reached the target sample size based on an a priori power analysis), the results are more likely to generalize to other samples than the typical study that uses a single sample. In general, the results across both samples were comparable. The differences in results tended to occur in the strength of a relationship and not in terms of the direction of a relation.

Future Research

From a theoretical perspective, the results provide support for Reward Sensitivity Theory in the context of course decision making. Based on the connection between person and course attributes established in this study, investigators may profitably focus on examining three issues. First, the successful use of individual differences based on Reward Sensitivity Theory to predict course ratings suggests that additional predictor development is warranted. Second, the use of course preference ratings as a proxy variable for criteria of greater interest in this study and other studies (Kerin et al., 1975; Taylor et al., 2004) highlights the need to consider and use additional criteria (e.g., actual course selection decisions, grades associated with a course selection decision). Third, a theory connecting person attributes, course attributes, and course selection decisions is needed to organize existing research and to guide future developments in a coherent and systematic approach.

The present study extended the examination of the basic tenets of Reward Sensitivity Theory to behavior in the context of a common activity; namely, course selection preferences. The complexity of the findings from this study suggests that more attention should be given to the development of valid predictor and criterion measures. In the predictor domain, individual differences in reward and punishment sensitivity appear to conceptually overlap with more macro-level constructs such as promotion and prevention focus (Higgins et al., 2001) and broader approach-avoidance motivational orientations (e.g., Elliot & Thrash, 2002; Kanfer, 1990; Kanfer & Heggestad, 1997; Kanfer & Heggestad, 1999). Regulatory Focus Theory (see Higgins et al., 2001) bears many similarities to Reward Sensitivity Theory. Similar to Reward Sensitivity Theory, two systems are presented in Regulatory Focus Theory. The human promotion system seeks the presence of positive outcomes and is concerned with obtaining objectives related to nurturance, accomplishment, and advancement. The human prevention system seeks the absence of negative outcomes and is concerned with ensuring security, safety, and the fulfillment of responsibilities. Researchers should consider comparing the predictive efficiency of the behavioral inhibition system and the behavioral activation system against the predictive efficiency of the human promotion system and the human prevention system.

More broadly, Elliot and Thrash (2002) demonstrated that the behavioral inhibition system and behavioral activation system are among several person characteristics that may be represented within an approach and avoidance temperament framework that also includes personality traits, affective dispositions, and motivational orientations (see also Kanfer & Heggestad, 1997). Consistent with Reward Sensitivity Theory, for approach attributes, positive and desirable events direct behavior, whereas for avoidance attributes, negative and undesirable events direct behavior. A more integrated approach of motivation and personality can be used to refine predictors based on theoretical inconsistencies and research findings among the related approach and avoidance concepts. For example, Gray (1990) indicated that the behavioral inhibition system is activated by novel stimuli, whereas Elliot and Thrash countered that avoidance and approach attributes are sensitive to different types of novel stimuli. Thus, researchers may profit from examining parallel developments within the broader approach-avoidance literature.

Results obtained in the pilot study provided support for a connection between Reward Sensitivity Theory and two learning styles: surface and deep processing approaches to learning. Students who resort to using surface level processing, out of a fear of failure, focus on just the material that will be tested and utilize simple learning strategies such as rote memorization (Biggs, 1987). Students who utilize deep processing approaches, out of an intrinsic interest in the content, attempt to maximize learning opportunities. The course features that were categorized as aversive due to the negative correlations between the course feature ratings and punishment sensitivity appear to be course features that surface processors would avoid when selecting a course (e.g., tests require a demonstration of understanding, instructor strays from topic), and the course features that were categorized as appetitive due to the positive correlations between the course feature ratings and reward sensitivity appear to be course features that deep processors would seek when selecting a course (e.g., self-confident instructor, exciting course). In other words, there appears to be a potential connection between the behavioral inhibition system and engaging in surface level processing and the behavioral activation system and engaging in deep level processing. Addition research is needed to determine the degree of association between the behavioral inhibition system, behavioral activation system, and the learning styles.

Although there has been a substantial amount of research conducted on course selection decisions made based on course content, such as whether or not to take a mathematics course or an English course (Marsh & Yeung, 1997; Meece et al., 1990), there has been surprisingly little research examining how course features influence students' course selection decisions. To some extent, the disparity in the amount of research may have resulted from the ease of organizing course content into a taxonomy in contrast to the difficulty of organizing course features into a usable framework. Course content, for the most part, is easily organized into content areas based on areas of study (e.g., mathematics, English) or departmental course offerings (e.g., psychology courses versus sociology courses). A similar taxonomy of course features is needed to advance research on course selection decisions. The utility of a particular taxonomy would ultimately depend on the design of a study. The pilot study was conducted to classify course features as appetitive, neutral, or aversive as the main study examined the predictive validity of the personality system derived from the Reward Sensitivity Theory. Further consideration of how to organize course features into a meaningful taxonomy is needed to further advance research examining course selection decisions.

As research progresses in the examination of the determinants of course selection decisions, the criterion should ultimately be actual course selection decisions as opposed to ratings of course descriptions. Course ratings are appropriate to use when establishing the relationship among predictors and criteria. Future research will need to determine whether the results of this study generalize to actual course selection decisions. Although ratings of hypothetical course descriptions allow for greater experimental control, the use of course selection decisions as the criterion allows for an examination of an important life decision made repeatedly over the lifespan.

The results of the study indicate that individual differences in punishment sensitivity are associated with rating courses more negatively on a negatively worded rating scale and individual differences in reward sensitivity are associated with rating courses more positively on a positively worded rating scale. To some extent, these findings may underlie a bias in processing. That is, punishment sensitivity may be associated with a propensity for thinking about courses in terms of the aversive aspects of the courses and having a more negative evaluation of the courses, and reward sensitivity may be associated with a propensity for thinking about courses in terms of the appetitive aspects of the courses and having a more positive evaluation of the courses. In general, a negative bias in processing may result in lower expectations for the course, less enjoyment during the course, and lower end of the semester course ratings, which may also contribute to lower grades and attendance rates. Conversely, a positive bias in processing may result in higher expectations, greater enjoyment, and higher end of the semester course ratings, which may translate into higher grades and attendance rates. As a result, students with a higher standing on punishment sensitivity may profit from bias reduction training. A method to investigate the potential bias that results from different levels of punishment and reward sensitivity is to examine the extent to which pre-training that attempts to attenuate individual differences related biases in attention and perception of course attributes attenuates the relationship between reward and punishment sensitivity and course ratings.

On the other hand, the differences in information processing associated with punishment and reward sensitivity may serve an adaptive function for both sensitivities. For example, as a vast array of potentially appetitive and aversive stimuli hinge on each course selection decision, the negative evaluations associated with punishment sensitivity may prepare students for the potential aversive stimuli and the positive evaluations associated with reward sensitivity may prepare students for the potential appetitive stimuli. Additional research is needed to determine whether there is an optimum match between course features, person attributes, and course selection decisions, and whether punishment and reward sensitivity lead to adaptive or maladaptive processing and course selection decisions. In this respect, additional criteria may also be examined with respect to course selection decisions. For example, how do course and person attributes affect students' grades, attendance, and chances of graduating? Does selecting courses with greater degrees of fit result in higher grades, attendance rates, and graduation percentages?

Researchers examining the association of course and person attributes with course selection decisions have not developed a theory. However, a theory is needed to guide the selection of important predictors, to layout the interconnection among predictors and paths to criteria, to organize course features into a meaningful taxonomy, and to determine how person and course attributes affect course selection decisions and other related outcomes of importance.

APPENDIX A

INTERACTION PLOTS

The interaction plots were created using the *SIMPLE-1* syntax written for SPSS by O'Connor (1998; see Figure 1 though Figure 10). Each plot computes simple slopes for three levels of the moderator— one standard deviation below, the mean, and one standard deviation above. To maintain the ease of interpretation of the plots and simple slopes, uncentered variables were used with the *SIMPLE-1* syntax (cf. Aiken & West, 1991). As discussed earlier in the Results section for the main study, only the interaction plots that present results from the ASU sample or the Georgia Tech sample (not the combined sample) are discussed below.

The first two plots in Figure 1 present the influence of BAS on two positively-toned ratings with BIS as the moderator for the ASU sample. At high levels of BIS, BAS positively predicts the ratings. As BIS decreases, the influence of BAS decrease, which is the opposite of what is suggested by the joint subsystems hypothesis (Corr, 2001). The third plot presents the influence of BIS on a negatively-toned rating with BAS as the moderator for the ASU sample. At high levels of BAS, BIS negatively predicts the negatively-toned rating. As BAS increases, the influence of BIS decreases slightly. This is consistent with what is suggested in the joint subsystems hypothesis.

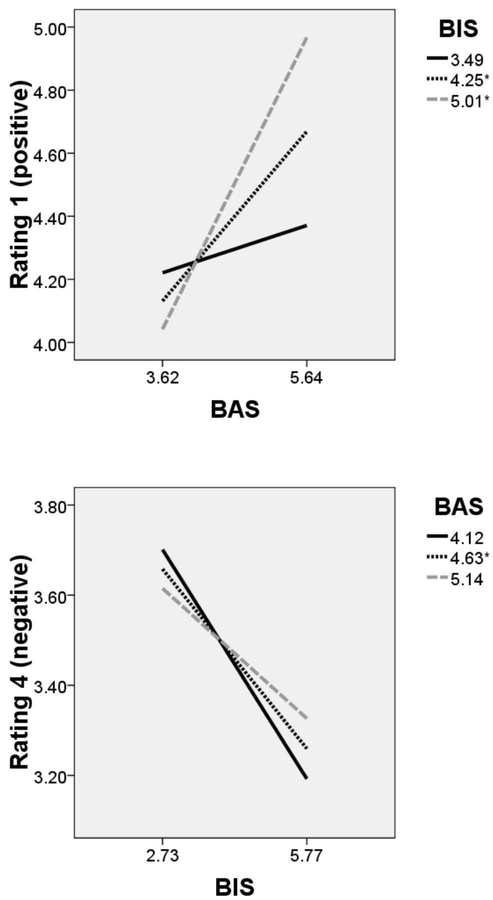

Figure 1. Interaction plots of BIS and BAS on course ratings (ASU sample).

The first three plots in Figure 2 present the influence of BAS on three positively-toned ratings with BIS as the moderator for the Georgia Tech sample. Counter to the joint subsystems hypothesis in the first two plots, BAS is negatively related to the positively-toned ratings at low levels of BIS. As BIS increases the effect size of the influence of BAS on the positively-toned ratings increases and is positive at high levels of BIS. In the third plot, the effect of BAS on the positively-toned rating is near zero at low levels of BIS and the size of the effect increases in a positive direction as BIS increases, which is essentially the opposite of what the joint subsystems hypothesis suggests. The last two plots in Figure 2 present the influence of BIS on the negatively-toned ratings with BAS as the moderator for the Georgia Tech sample and conform to predictions made in the joint subsystems hypothesis as BIS is negatively associated with the negatively-toned ratings and the size of the effect attenuates as the level of BAS increases.

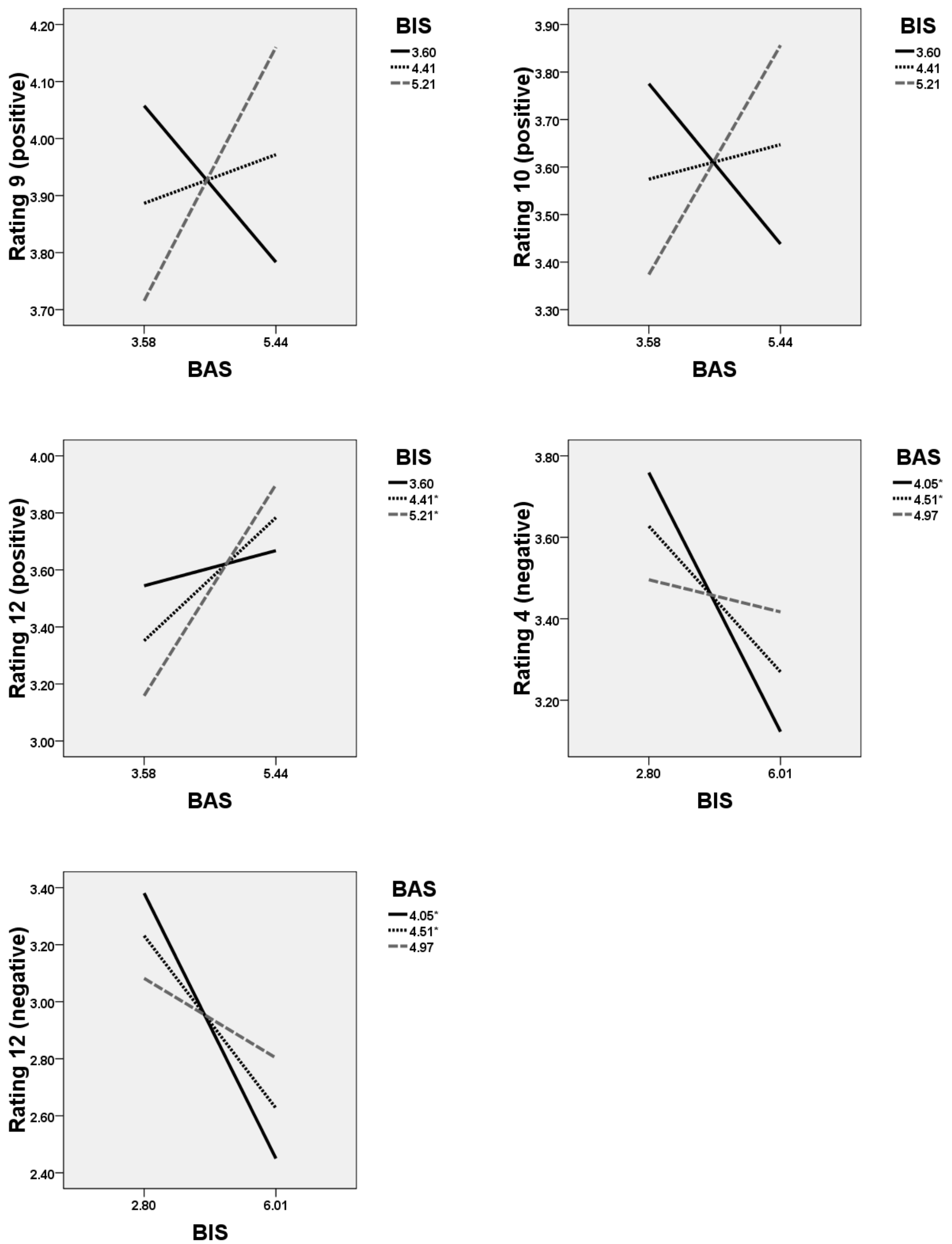

Figure 2. Interaction plots of BIS and BAS on course ratings (Georgia Tech sample).

The first plot in Figure 3 presents the influence of BAS+ on a positively-toned rating with BIS+ as the moderator for the ASU sample. The plot conform to predictions made in the joint subsystems hypothesis as the correlation between BAS+ and the positively-toned rating is positive at low levels of BIS+ and the size of the effect decreases slightly as the level of BIS+ increases. The next plot in Figure 3 presents the influence of BIS+ on a negatively-toned rating with BAS+ as the moderator for the ASU sample. In this interaction plot, BIS is negatively related with the negatively-toned rating at low levels of BAS+. The influence of BIS+ on the negatively-toned rating decreases as the level of BAS+ increases. This plot provides an excellent representation of the predictions made in the joint subsystems hypothesis as the relationship between BIS+ and the negatively-toned rating is essentially zero at high levels of BAS+.

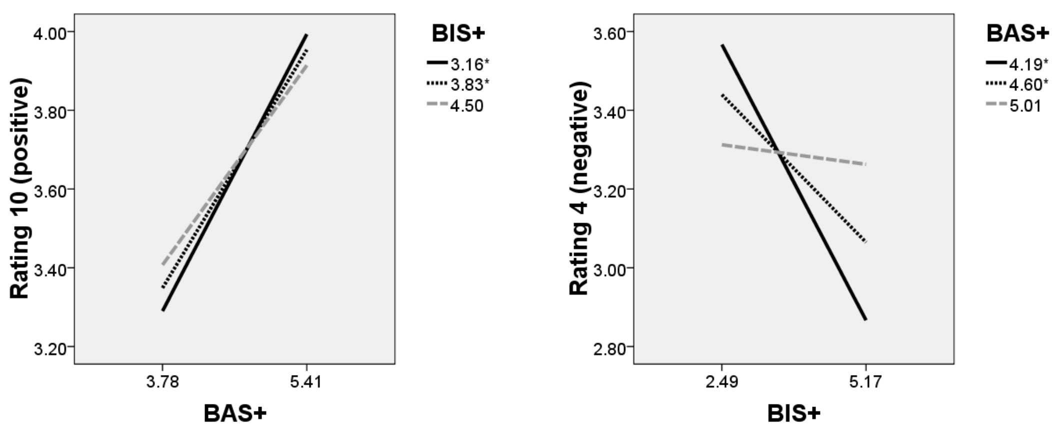

Figure 3. Interaction plots of BIS+ and BAS+ on course ratings (ASU sample).

All ten plots in Figure 4 present the influence of BAS+ on ten positively-toned ratings with BIS+ as the moderator for the Georgia Tech sample. This series of interaction plots do not conform to predictions made in the joint subsystems hypothesis. In general, at low levels of BIS+, the correlation between BAS+ and the positively-toned ratings is near zero. As the level of BIS+ increases, the correlation between BAS+ and the positively-toned ratings increases in a positive direction.

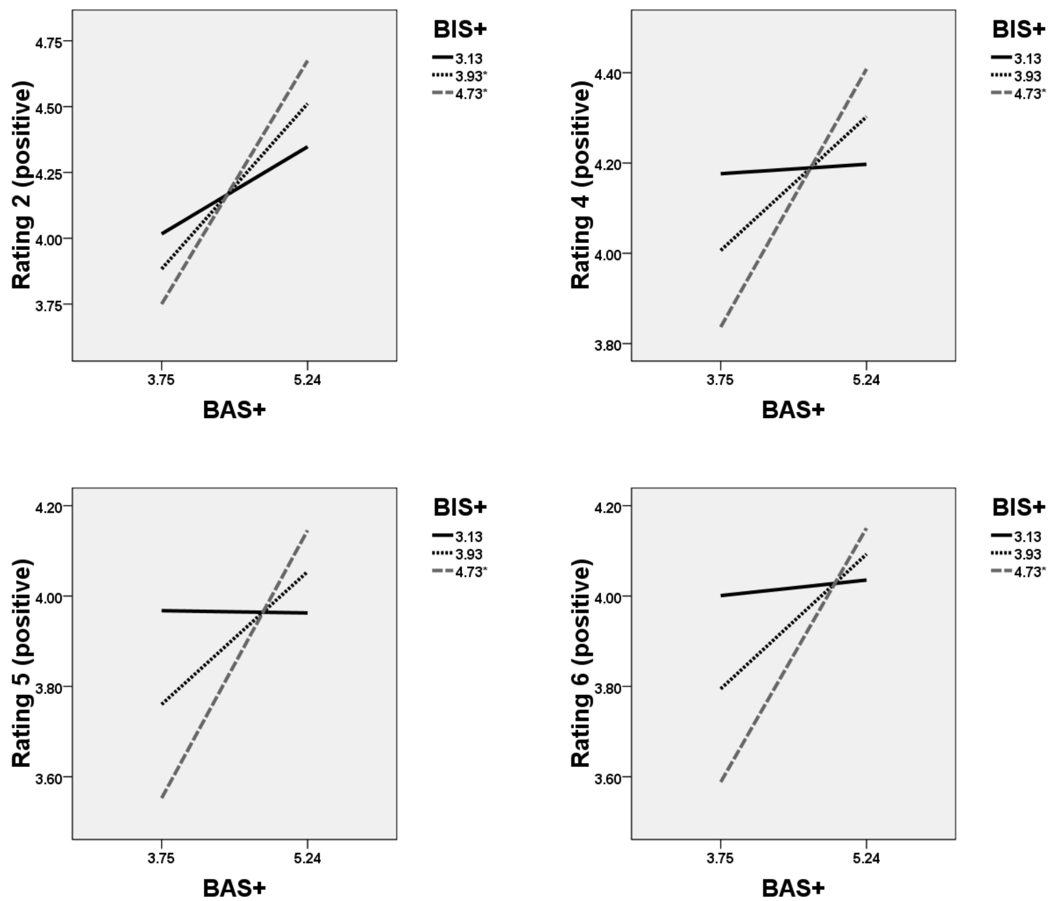

Figure 4. Interaction plots of BIS+ and BAS+ on course ratings (Georgia Tech sample).

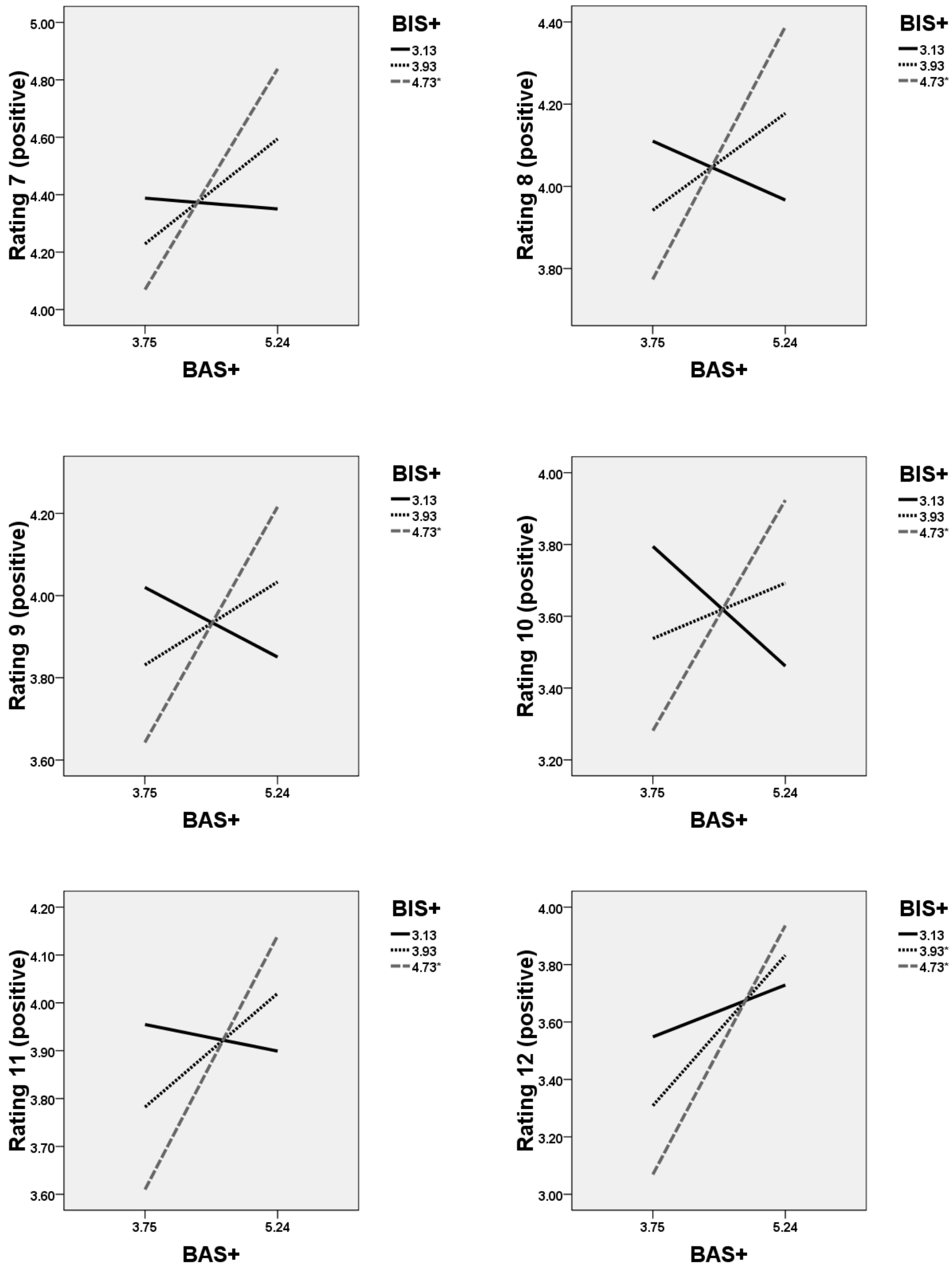

Figure 4 (continued).

The three plots in Figure 5 present the influence of Extraversion on three positively-toned ratings with Neuroticism as the moderator. These three plots conform to predictions made in the joint subsystems hypothesis. At low levels of Neuroticism, the effect size of the correlation between Extraversion and the positively-toned ratings is in the positive direction. The correlation between Extraversion and the positively-toned ratings attenuates as the level of Neuroticism increases.

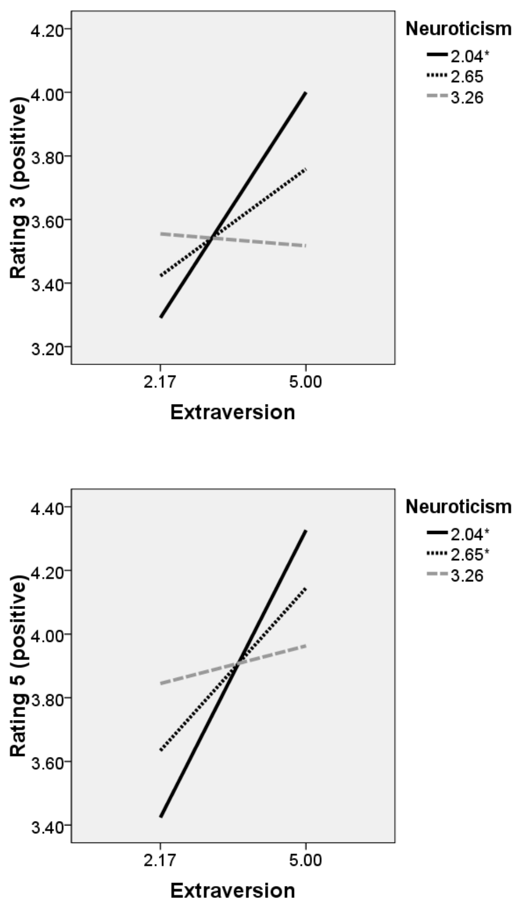

Figure 5. Interaction plots of Neuroticism and Extraversion on course ratings (ASU sample).

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